PART 1 OF EXHIBIT 2

IN THE UNITED STATES COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA

In re. Uber Technologies, INC., Passenger Sexual Assault Litigation	Case No. 3:23-md-03084-CRB

Updated Expert Report of Lacey R. Keller ("Updated Keller Report")

Dated: December 2, 2025

Confidential and Subject to Protective Order

I. Assignment

1. Plaintiffs' Counsel asked me to update the "Expert Report of Lacey R. Keller" and its appendices that I filed on September 26, 2025 ("Opening Report") due to two data productions related to the Flack system that Uber provided to Plaintiffs' Counsel on October 13, 2025 and October 17, 2025. This updated report entirely replaces my Opening Report.

2. As described in my Opening Report, my assignment was to review documents and data produced in this litigation to calculate the number of, rates of, and trends related to Sexual Assault and Sexual Misconduct ("SA/SM")[1] Incidents reported to Uber between 2017[2] and 2024, as well as Uber's investigations of those incidents and Uber's communications about the incidents in Uber's U.S. Safety Reports. More specifically, Plaintiffs' counsel asked me to analyze the number of and compare SA/SM Incidents that Uber:

   2.1. disclosed in Uber's U.S. Safety Reports released for 2017-2018, 2019-2020, and 2021-2022 (collectively referred to in this report as "Uber's U.S. Safety Reports");[3]

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[1] In this report, I use the following terminology to refer to the Sexual Assault and Sexual Misconduct incidents in the data I reviewed: Sexual Assault incidents may be referred to as "SA Incidents," Sexual Misconduct incidents may be referred to as "SM Incidents," and Sexual Assault and Sexual Misconduct incidents may be referred to collectively as "SA/SM Incidents." I provide a complete list of terminology and definitions in Updated Keller Report Appendix B.

[2] With 24,582 incidents in the Flack SA/SM Incident Data with a trip_request_timestamp_local date prior to 2017, the data provided from 2013 to 2017 appeared to be incomplete. Internal documents from Uber (e.g., UBER_JCCP_MDL_004202739) show that reports stored in ZenDesk - a system used by Uber until 2016 (Deposition of Katherine McDonald, 4/25/2025) - were previously included within the Flack system. The ZenDesk fields were empty in the Flack SA/SM Incident Data produced by Uber. Uber's Flack system also does not contain data for trips that were null for 'trip_uuid,' even though those same trips may be in the Bliss or Jira databases (*See* Deposition of Todd Gaddis 11/7/2025 at 75). Finally, Uber did not provide 2025 data or totals prior to 2017 in the Updated Flack Incident Report Classification Data, which would have allowed me to validate this data. Therefore, I did not include this data in my analysis.

[3] "Uber's US Safety Report." Uber. https://www.uber.com/us/en/about/reports/us-safety-report/' The US Safety Report covering 2017-2018 was released on December 5, 2019; 2019-2020 was released on June 30, 2022; 2021-2022 was released on August 30, 2024 (Deposition of Katherine McDonald, 4/24/2025, p. 137-139; Deposition of Katherine McDonald, 4/24/2025, Exhibit 3111).

2.2. tabulated from its Bliss and Jira systems in response to interrogatories (referred to in this report as "Bliss/Jira Incident Report Classification Data");[4]

2.3. tabulated from its Flack system in response to interrogatories (referred to in this report as "Flack Incident Report Classification Data");[5]

2.4. raw data on Sexual Assault and Sexual Misconduct that Uber produced from its Flack system (referred to in this report as "Flack SA/SM Incident Data").

3. Furthermore, Plaintiffs asked me to conduct data analyses related to specific Uber Drivers reported for SA/SM Incidents[6] involving the Bellwether Plaintiffs.[7] I analyzed data that Uber produced related to these Drivers to catalog the type of data and information that Uber collected on Drivers who were reported for SA/SM Incidents. These analyses are detailed in Updated Keller Report Appendix D. The same analysis could be applied to any Driver who was reported for an SA/SM Incident.

4. Plaintiffs asked me to review and analyze data and documents related to Uber's Safety Risk Assessed Dispatch ("S-RAD"), a machine learning algorithm that was developed at Uber by data scientists that "leverages a variety of trip, driver, and rider-level predictors to detect driver-rider matches with elevated risk of sexual assaults."[8]

5. I have included demonstrative charts and images in this report to aid in understanding certain analyses. I reserve the right to use different or modified demonstratives at trial as appropriate. I have offloaded high-resolution images and CSV files containing the raw data

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[4] *In re Uber Technologies, Inc., Passenger Sexual Assault Litigation* (Case No.: 3:23-MD-03084 CRB) Supplemental Information Provided by Defendants Pursuant to the Parties' Agreement, Dated April 4, 2025; *In re Uber Technologies, Inc., Passenger Sexual Assault Litigation* (Case No.: 3:23-MD-03084 CRB) Incident Report Classification for 2023-2024.
[5] *In re Uber Technologies, Inc., Passenger Sexual Assault Litigation* (Case No.: 3:23-MD-03084 CRB) "Incident Report Classification of Dominant Tickets for 2017-2024".
[6] Defined in Updated Keller Report Appendix B.
[7] Defined in Updated Keller Report Appendix B.
[8] UBER_JCCP_MDL_003306684 at 3306697.

underpinning each image to Updated Keller Report Appendix E, which is available in "Bucket 1m" in the AWS Secure Environment.[9]

6. Finally, I include within my report:

6.1. Updated Keller Report Appendix A - Methodology

6.2. Updated Keller Report Appendix B - Definitions

6.3. Updated Keller Report Appendix C - Qualifications and Remuneration

6.4. Updated Keller Report Appendix D - Driver Profiles

6.4.1. Updated Keller Report Appendix D1 - Driver Profiles (Excel Files)[10]

6.4.2. Updated Keller Report Appendix D2 - Driver Flack SA/SM Incident Data[11]

6.5. Updated Keller Report Appendix E - High Resolution Images and CSVs[12]

6.6. Updated Keller Report Appendix F - S-RAD Inputs[13]

6.7. Updated Keller Report Appendix G - Materials Considered

6.8. Updated Keller Report Appendix H - Code Disclosures[14]

6.9. Updated Keller Report Appendix I - Long Form CSVs[15]

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[9] It is typically my practice to offload my code and data into an AWS S3 bucket (i.e., folder) for production. For Defendants' convenience, I have disclosed through "Bucket 1m" all code and any data that was uploaded into the "Bucket 2" ingress. These offloads are timestamped and cannot be deleted by Plaintiffs. Pursuant to the agreement between Uber and Plaintiffs' Counsel, I am not re-producing data that Uber had uploaded in "Bucket 1" back to Uber through "Bucket 1m," including the SA/SM Incident Data, Interrogatory No. 28, Interrogatory No. 16/2 and Interrogatory No. 16/29 Addendum.
[10] I have offloaded these files into "Bucket 1m" in the AWS Secure Environment.
[11] I have offloaded these files into "Bucket 1m" in the AWS Secure Environment.
[12] I have offloaded these files into "Bucket 1m" in the AWS Secure Environment.
[13] Provides a historical timeline of the features included in the S-RAD model from the first developed versions through the present.
[14] I have offloaded these files into "Bucket 1m" in the AWS Secure Environment.
[15] I have offloaded these files into "Bucket 1m" in the AWS Secure Environment.

6.9.1. "Insufficient Information" and "Parent Category Use Tracking" Trip UUIDS: insufficient_information_incidents_table.csv, parent_category_usage_tracking_incidents_table.csv

6.9.2. Non-Consensual Sexual Penetration reports from the Flack SA/SM Incident Data not in Interrogatory No. 28: sexual_penetration_reports_not_in_rog28_from_flack.csv

6.9.3. Trip UUIDs that are present in Interrogatory No. 28 and in the Jira/Bliss SA/SM Incident Data, but are not present in the Flack SA/SM Incident Data: trips_in_rog_28_and_jira_bliss_not_in_flack.csv

6.9.4. Attachment Sample Trip UUDs that are not in the Flack SA/SM Incident Data: sample_trips_not_in_flack.csv

6.9.5. The number of trips with reports, counts of reports against Drivers and Riders, and the percentage of trips with reports against each party type for every year and incident Subcategory in the Flack SA/SM Incident Data: all_incidents_reported_against_by_year_subcat_table.csv

6.9.6. For each city in the Flack SA/SM Incident Data, the number of trips with SA/SM Incident reports and rankings based on the number of reports, the number of reports in the five Safety Report Subcategories, and the number of reports for Rape or Attempted Rape: cities_by_sasm_pct_ranking_table.csv

6.9.7. The number of trips in the Flack SA/SM Incident Data with reports against Drivers, grouped by day of week, hour of incident, incident Subcategory, and severity level: day_time_of_day_heat_bars_figure_flack_with_subcategory_and_level.csv

6.9.8. Incident Driver UUIDs of Drivers with multiple Rape or Attempted Rape incidents reported against them in the Flack SA/SM Incident Data and the Trip UUIDs, trip request time, and Subcategories of these incidents:

Driver_trips_with_multiple_penetration_or_attempted_penetration.csv

6.9.9. Unresolved reports from the Flack SA/SM Incident Data: unresolved_flack_sasm_incidents_table.csv

II. Qualifications

7. I am a data scientist with over 15 years of practical work experience in the field, including teaching, speaking, and publishing. I am the co-founder of MK Analytics, Inc., a consulting firm that assists non-profits, government entities, and law firms in implementing and conducting data-driven initiatives, investigations, and analyses. Before founding MK Analytics, I founded the Research and Analytics Department at the New York State Office of the Attorney General, the first of its kind in the nation, leading a team that employed cutting-edge data analysis in high-profile cases. I am an adjunct professor at Washburn University, where I co-teach the capstone project course and an introductory course on data information systems, analysis, and database management. I have so far published nearly a dozen works and delivered over two dozen speaking engagements related to Data Mining and Analysis, including guest lecturing at Washburn University School of Business, Brooklyn Law School, Columbia Law School, Yale Law School, and the University of Missouri School of Accountancy. I hold a Master of Economics from the New School and a Bachelor of Business Administration from Washburn University. Updated Keller Report Appendix C outlines my full professional history, prior depositions and trial testimonies, and compensation on this matter.

8. My opinions are held to a reasonable degree of professional certainty and are based on my professional experience and training, as detailed in Updated Keller Report Appendix C, as well as consideration of publicly available data and information in addition to documents and data produced in this litigation, as described in the updated Materials Considered (Section IV) portion of this report. The staff that worked under my direction had full and complete access to the documents and data noted in my Materials Considered (Updated Keller Flack Report Appendix

G). I have provided all of my source code, including scripts, queries, and other materials related to my analysis.

9. My analysis and the opinions in my report considered the data that Uber produced in this litigation as of the date of this report. I reserve the right to amend or supplement the facts and opinions upon which I am expected to testify as additional data and information are made available.

III. Summary of Opinions

10. Based on my analyses (as described herein), my review of documents and data, and my professional experience, I hold the following opinions:

10.1. **Opinion 1: Uber's Updated Flack Incident Report Classification Data and Flack SA/SM Incident Data show hundreds of thousands of Sexual Assault and Sexual Misconduct Incidents reported to Uber from 2017 through 2024 in the United States.**[16] Uber's Updated Flack Incident Report Classification Data shows 546,420 SA/SM Incidents reported from 2017 through 2024. From 2017 through 2024, an SA/SM Incident was reported to Uber the equivalent of every eight minutes. A Rape[17] or Attempted Rape[18] incident was reported to Uber [redacted]. Both the number and rate[19] of Rape incidents [redacted]. In 2024, Uber received [redacted] according to the Updated Flack Incident Report Classification Data.

[16] The Flack SA/SM Incident Data and the Updated Flack Incident Report Classification Data completely align when comparing monthly report volumes by Category and Subcategory for 2017 through 2024.
[17] Defined in Updated Keller Report Appendix B.
[18] Defined in Updated Keller Report Appendix B.
[19] Defined as the number of SA/SM Incidents divided by the Number of Completed Rides Trips in the United States.

10.2. **Opinion 2: Uber's U.S. Safety Reports disclosed no more than 3.2% of Sexual Assault and Sexual Misconduct incident reports that Uber received, classified into SA/SM Incident Subcategories, and retained in Flack from 2017 through 2022 in the United States.** Uber published on its Safety Room blog that it had publicly disclosed 3% of the SA/SM Incidents reported from 2017 through 2022.[20] Uber's U.S. Safety Reports disclosed the number of SA/SM Incidents in the five Subcategories that Uber referred to publicly as the "most serious."[21] However, Uber tracked SA/SM Incident reports and categorized them into Uber's Sexual Violence and Sexual Misconduct Taxonomy, which contains 21 publicly disclosed Subcategories.[22] In total, the Updated Flack Incident Report Classification Data shows Uber received, classified into SA/SM Incident Subcategories, and retained in Flack reports of 392,828 SA/SM Incidents from 2017 through 2022 in all Subcategories, including [redacted] Uber categorized into Subcategories it classified as "Serious SA/SM" but did not disclose in its Safety Reports. Uber's U.S. Safety Reports disclosed 12,522 SA/SM Incidents for those same years. Uber's SA/SM Incident counts also show that it received, classified into SA/SM Incident Subcategories, and retained in Flack 153,592 SA/SM Incident reports from 2023 through 2024 ([redacted] in the 13 Subcategories that Uber classified as "Serious SA/SM"). Accounting for SA/SM Incidents from 2023 through 2024, Uber has currently disclosed 2.3%[23] of all SA/SM Incidents retained in Flack from 2017 through 2024, or [redacted][24] of the SA/SM Incidents that Uber referred to internally as "Serious SA/SM."

[20] In response to an August 6, 2025 New York Times article, (https://www.nytimes.com/2025/08/06/business/uber-sexual-assault.html), Uber stated that the incidents it disclosed were limited to the "3% most serious." ("Uber's record on safety is clear." Uber Newsroom, https://www.uber.com/newsroom/ubers-safety-record/).
[21] Uber's U.S. Safety Reports 2017-2018, 2019-2020, and 2021-2022.
[22] *See* Updated Keller Report Appendix B for information on which Subcategories were contained in each data source.
[23] 12,522 / 546,420 = 2.3%.
[24] 12,522 [redacted]

10.3. **Opinion 3: Uber internally discussed that there were "precursors"[25] to Sexual Assault and Sexual Misconduct incidents, but it did not disclose that information in U.S. Safety Reports.** Uber's internal documents indicate Uber analyzed certain trends, patterns, and "precursors" along with their correlation with increased rates of SA/SM Incidents, including: the day of week and time of day of the trip, the proximity to bars, opposite gender Driver-Rider pairings, prior SA/SM reports, "Feedback tags", and factors related to the timing of deactivation.[26] Based on my review of the Flack fields list in Todd Gaddis's August 18, 2015 declaration and my review of documents and testimony in this case, it is my opinion that Uber maintains data sufficient to analyze these trends and patterns; however, as of the date of this report, Uber still has not produced this information, including as part of its Flack productions.

10.4. **Opinion 4: Uber tracked in Flack which of its Drivers had prior SA/SM Incidents and internally discussed that having a prior SA/SM Incident made a Driver more likely to be reported for SA/SM again.** Uber has identified a history of prior SA/SM Incidents as a "pattern" related to future SA/SM Incidents.[27] In July 2017, Uber's internal analyses showed that Drivers with at least one previous SA/SM Incident were [redacted] to be reported in the future for Sexual Assault.[28] Additionally, Drivers with previous SA/SM Incident reports were more likely to have "patterns of escalation,"[29] meaning a more serious SA/SM Incident (according to Uber's taxonomy) in the future. Approximately [redacted] SA/SM Incidents reported against Uber Drivers involved Drivers who had already been reported once to Uber for SA/SM, according to the Flack SA/SM Incident Data.

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[25] UBER_JCCP_MDL_000356814.
[26] UBER000204698; UBER_JCCP_MDL_001755017; UBER_JCCP_MDL_003504225; UBER_JCCP_MDL_000258366; UBER_JCCP_MDL_002249692; UBER_JCCP_MDL_000031720; UBER_JCCP_MDL_00330668; UBER_JCCP_MDL_000964270; UBER_JCCP_MDL_000014232; August 25, 2025 Deposition of Greg Brown, Exhibit 1932.
[27] UBER_JCCP_MDL_000964270.
[28] UBER_JCCP_MDL_001687315; June 25, 2025 Deposition of Sunny Wong at 208-209; June 17, 2025 Deposition of Greg Brown at 32-39. Uber did not provide the data necessary to perform this analysis independently.
[29] UBER_JCCP_MDL_000014232.

10.5. **Opinion 5: Uber's Flack system includes specific columns and fields for data on auditing, reporting parties (i.e., Drivers, Riders), the time and day of SA/SM Incident reports, and city-level information.** Uber audited a vast majority ([redacted]) of the 546,420 trips retained in Flack that had SA/SM Incidents. Uber also retained data in Flack on the reporting party of SA/SM incidents, which showed the majority [redacted] of Rape and Attempted Rape incidents were reported against Drivers, as well as data on the time and day of SA/SM Incidents, which showed a disproportionate volume of SA/SM Incidents occurred during Weekend Late Nights. Finally, Flack data contained Uber-created "city" designations that do not align with local, state, or federally drawn city boundaries, which precluded me from performing any per capita calculations for Uber's "cities." Uber also did not produce trip volume for these "city" designations, which precludes me from completing an analysis of SA/SM Incident rates at the city level.

10.6. **Opinion 6:[30] Uber cultivated a data-rich environment from its founding, and implemented a machine learning algorithm nearly a decade later to "prevent sexual assaults."[31]** When Uber dispatches a Driver to a Rider, S-RAD is the only way Uber takes into account, and attempts to reduce, the risk of SA/SM Incidents.[32] Since Uber deployed S-RAD in 2022, Uber has applied S-RAD at a [redacted] for all U.S. trips "in aggregate."[33] In other words, approximately [redacted] of Uber trips are not evaluated as to the risk of possible SA/SM Incidents.

[30] S-RAD analysis remains the same as in my September 26, 2025 Expert Report, as the new Flack data productions did not impact S-RAD.
[31] UBER JCCP MDL 001144266; UBER JCCP MDL 001101922; UBER_JCCP_MDL_003306684; UBER_JCCP_MDL_001730324; UBER_JCCP_MDL_003224079.
[32] June 25, 2025 Deposition of Sunny Wong at 232:18-233:9.
[33] UBER_JCCP_MDL_005025910; Deposition of Sunny Wong, 6/25/2025, p. 255.

10.7. **Opinion 7: I confirmed Uber collected data and information on the Drivers of the Bellwether trips and the Bellwether incidents, including tracking Plaintiff SA/SM Incidents in the Flack SA/SM Incident Data.**[34] I observed that this data resembled the information in other documents and data produced. For example, Drivers like Hassan Turay had two prior reports of SA/SM Incidents that occurred prior to the Plaintiff's trip on November 15, 2023.[35] I have offloaded those records into Updated Keller Report Appendix D1 - Driver Profiles (Excel Files) and Updated Keller Report Appendix D2 - Driver Flack SA/SM Incident Data.

IV. Materials Considered

11. The sections below discuss the datasets and documents that I considered in writing this report and forming my opinions.

A. Uber's Internal Documents

12. I reviewed documents Uber produced in this litigation to form my opinions in this report. I had complete access to documents produced in this litigation through Everlaw. Updated Keller Report Appendix A provides more information on the documents review and considered items. The Bates numbers for all considered items have been provided in Updated Keller Report Appendix G.

B. Uber's U.S. Safety Reports

13. Uber has published three Uber U.S. Safety Reports covering the years 2017-2018, 2019-2020, and 2021-2022. The reports were released as follows: 2017-2018 on December 5, 2019; 2019-2020 on June 30, 2022; and 2021-2022 on August 30, 2024.[36] Uber has not issued a report for 2023-2024 as of the date of this report. Uber has never issued a report disclosing Flack SA/SM Incident data for years prior to 2017.[37]

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[34] I was able to identify all but two of the Bellwether trips in the Flack SA/SM Incident Data: Alyssa Lowe and Kaytlyn Edins.
[35] UBER-MDL3084-DFS00159600.
[36] Deposition of Katherine McDonald, 4/24/2025, p. 137-139; Deposition of Katherine McDonald, 4/24/2025, Exhibit 3111.
[37] July 8, 2025 Deposition of Todd Gaddis, p. 18.

C. Produced Data

14. I considered the following datasets and related documents produced by Uber, as detailed in the paragraphs below.

i. Defendants' Processed Data (Interrogatory Responses & Information Summaries in Rule 30(b)(6) Depositions)

15. **Interrogatories Nos. 1 through 8 ("Bliss/Jira Incident Report Classification Data," "Flack Incident Report Classification Data," "Updated Flack Incident Report Classification Data" and collectively, "Incident Report Classification"):**[38] In response to Plaintiffs' Interrogatories 1 through 8, on April 17, 2025, April 23, 2025, June 20, 2025, and September 12, 2025, Uber provided tables that quantified the number of SA/SM Incidents reported to Uber each month from 2017 through 2024 by Category and Subcategory. The April 17, 2025 document is titled "Information Provided by Defendants Pursuant to the Parties' Agreement, Dated April 4, 2025." The April 23, 2025 document is titled "Supplemental Information Provided by Defendants Pursuant to the Parties' Agreement, Dated April 4, 2025." The June 20, 2025 document was titled "Incident Report Classification for 2023-2024." Collectively, I refer to the data in the April 17, April 23, and June 20 documents as "Bliss/Jira Incident Report Classification Data." The September 12, 2025 document was titled "Incident Report Classification of Dominant Tickets for 2017-2024" and I referred to the data in my Opening Report as the "Flack Incident Report Classification Data." Uber made a fifth production of the Incident Report Classification Data, which contained 224 SA/SM incidents that were not included in the previous Flack Incident Classification Data Uber made on September 12, 2025. Uber produced this update to the Flack Incident Report Classification Data on October 13, 2025, alongside the first of two productions of Flack SA/SM Incident Data. I refer to this updated data as the "Updated Flack Incident Report Classification Data." Uber's Bliss/Jira Incident Report Classification Data

[38] Interrogatories 1 through 8 asked Uber to specify the number of Sexual Assault and Sexual Misconduct Incidents that Uber categorized into each Subcategory in Uber's Sexual Assault and Sexual Misconduct Taxonomy for every month from 2017 through 2024 (Defendants Uber Technologies, Inc., Rasier LLC and Rasier-CA, LLC's Amended Responses to Plaintiffs' Second Set of Interrogatories, 5/1/2025, In Re: Uber Technologies, Inc., Passenger Sexual Assault Litigation, Case No. 23-md-03084-CRB (hereinafter "Amended Responses"), p. 5-11).

provided comparable results to the analysis based on the Updated Flack Incident Report Classification Data; however, I analyze the Updated Flack Incident Report Classification Data in this report because Uber did not de-duplicate Bliss/Jira Incident Report Classification Data[39] and because Uber's corporate witness testified that Uber uses Flack to obtain reliable data about SA/SM Incidents.[40]

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[39] In the "In re Uber Technologies, Inc., Passenger Sexual Assault Litigation (Case No.: 3:23-MD-03084 CRB) Information Provided by Defendants Pursuant to the Parties' Agreement, Dated April 4, 2025" Uber makes the following statement:

> *… It is also important to note that this information does not, and cannot, reflect the number of incidents Uber placed into each of the 21 categories because a single incident might be placed into several different categories at different stages during the intake, review, or audit processes—and indeed, a single incident may be reported via more than one reporter, or reporting channel. Therefore, the number of categorizations for incidents from a given month is not the same as the number of reported incidents from a given month. For this reason, the information included herein does not, and cannot, reflect that there were a certain number of incidents in a given month, nor does the information indicate that the sum total of categorizations is reflective of the total number of incidents. A single incident may result in multiple different categorizations. …*

Uber made a similar statement in "In re Uber Technologies, Inc., Passenger Sexual Assault Litigation (Case No.: 3:23-MD-03084 CRB) Incident Report Classification for 2023-2024." By summing the volume of reports by category (sum_volume) and comparing it to the "Total # of Unique Rides Trips with a Reported Incident"[sic] field provided (unique_volume) in "In re Uber Technologies, Inc., Passenger Sexual Assault Litigation (Case No.: 3:23-MD-03084 CRB) Supplemental Information Provided by Defendants Pursuant to the Parties' Agreement, Dated April 4, 2025" I am able to calculate the potential of duplication calculated as the (sum_volume - unique_volume) / unique_volume) due to multiple classifications by Uber per month. The maximum duplication in a single month during 2017-2022 is approximately 3.42%, the minimum is 0.06%, and the average is 1.54% (2017-2022) and 1.75% (2017-2024), with a larger percentage of duplication generally occurring in later years. Duplication of tickets is possible not only within a single month across Subcategories but also across multiple months. Uber did not provide an annual equivalent to the field "Total # of Unique Rides Trips with a Reported Incident."

[40] July 23, 2025 Deposition of Hannah Nilles at 64-69, 302-303.

16. **Interrogatory No. 16[41]/29[42] ("Interrogatory No. 16/29" and "Interrogatory No. 16/29 Addendum"):** In response to Plaintiffs' Interrogatory Numbers 16 and 29, Uber produced a list of 207,058 unique Driver UUIDs though the Secure Environment (produced May 1, 2025), as well as a supplemental response regarding 40,976 Drivers with the deactivation date and reason into the Secure Environment (produced June 6, 2025), and a June 10, 2025 declaration from Todd Gaddis. Although Uber provided these lists of deactivated Drivers who had one or more SA/SM Incidents reported against them, Uber has not identified a list of Drivers who were deactivated due to an SA/SM Incident or produced data that included the reason a Driver was deactivated. In other words, Uber has not produced data that definitively indicates whether deactivated Drivers were deactivated because of a specific SA/SM Incident report against them, or for some other reason. Uber claims it does not maintain deactivation data in a way that can be queried to determine whether a Driver is no longer active due to an SA/SM Incident or for another reason (e.g., deactivation request by Drivers themselves, expired document, issue with background check, violation of terms of service).[43]

[41] Interrogatory 16 asked Uber to identify Driver UUIDs within the Bliss/Jira SA/SM Incident Data of Drivers who were banned from the Uber platform at any time from 2009 to present for reasons referenced in Uber's U.S. Safety Report 2017-2018, limited to Independent Driver UUIDs contained in the incident report data produced to Plaintiffs via BDO (the Bliss/Jira SA/SM Incident Data). (Amended Responses, p. 28-29). Because Uber's responses were limited to the Bliss/Jira SA/SM Incident Data, the Driver UUID list it provided is limited to Drivers who were reported for an SA/SM Incident between 2017-2022 and were deactivated (for any reason) between 2017-2022.

[42] Interrogatory 29 asked Uber to identify Driver UUIDs within the Bliss/Jira SA/SM Incident Data of Drivers who were deactivated and not subsequently reactivated from the Uber platform as a result of any report of any SA/SM Incident categorized under any of the 21 Subcategories in Uber's Sexual Assault and Sexual Misconduct Taxonomy, including the date of deactivation. The Interrogatory was limited to Independent Driver UUIDs contained in the incident report data produced to Plaintiffs via BDO (the Bliss/Jira SA/SM Incident Data). (Amended Responses, p. 38). Because Uber's responses were limited to the Bliss/Jira SA/SM Incident Data, the Driver UUID list it provided is limited to Drivers who were reported for an SA/SM Incident from 2017 through 2022 and were deactivated (for any reason) from 2017 through 2022.

[43] Declaration of Todd Gaddis, 6/10/2025; Uber's Second Amended Responses to Plaintiffs' Second Set of Interrogatories, 5/28/2025.

17. **Interrogatory No. 28:**[44] In response to Plaintiffs' Interrogatory Number 28, Uber produced a list of trip UUIDs into the Secure Environment for each trip that resulted in an incident disclosed in any of Uber's U.S. Safety Reports as well as payment data (e.g., "Refunds and Appeasements (USD)," "Net (USD)," and "Gross (USD)"). Uber produced 12,522 trip UUIDs,[45] which aligned with the exact number of SA/SM Incidents disclosed in the Uber U.S. Safety Reports.

18. **Documents produced in conjunction with the July 11, 2025 Deposition of Todd Gaddis.**

    18.1. **"Weekday/Weekend Trip Volume per State per Year, 2012-2024" (Exhibit 1574 to July 11, 2025 30(b)(6) Deposition of Todd Gaddis):** Provides a table of completed trips by year and state from 2012 through 2024, broken out by weekday and weekend.

    18.2. **"Count of Drivers by Gender and by Year ('U.S.') 2012-2024" (Exhibit 1575 to July 11, 2025 30(b)(6) Deposition of Todd Gaddis):** Provides a table of the number of Drivers by gender and year from July 2012 through November 2024, broken out by "Male," "Female," "Unknown,"[46] and "Total."

    18.3. **"Rider Counts by Year 2012-2024 (Exhibit 1576 to July 11, 2025 30(b)(6) Deposition of Todd Gaddis):** Provides a table of the number of Riders by gender and year from 2012 through 2024, broken out by "Female," "Male," "Unknown," and "Total."[47]

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[44] Interrogatory 28 asked Uber to identify the amount of payment that Uber received for each trip (by trip UUID) that had a SA/SM Incident and was included in any of the following tables: Table 12 of Uber's U.S. Safety Report 2017-2018, Tables 13 through 17 of U.S. Safety Report 2019-2020, and Table 4 of U.S. Safety Report 2021-2022 (Amended Response, p. 37). Uber also produced a document on June 3, 2025 titled "Defs' Responses to ROG 28 Questions" to address questions about this data.

[45] However, 56 of the 'trip_uuids' that Uber provided did not match to 'trip_uuids' produced in any of the files in the Bliss/Jira SA/SM Incident Data. Uber has not explained these inconsistencies. My analysis could only consider trip UUIDs that were in Uber's list as well as in the Bliss/Jira SA/SM Incident Data.

[46] According to the document: *"Gender of driver may not be available for any number of reasons, including but not limited to: incorrect or missing transcription (by tech or by manual review) or missing driver's ID document data as a whole (either at driver's request to delete data or Uber's data retention policy)."*

[47] According to the document: *"Rider cohort is based upon those accounts who also have a driver account with an identified gender based on their provided document(s)."*

ii. Defendants' Raw Data on Sexual Assault and Sexual Misconduct Incidents ("Bliss/Jira SA/SM Incident Data" and "Flack SA/SM Incident Data")

19. On July 9, 2024, Judge Cisneros ordered Uber to produce data and documents related to SA/SM Incidents in the United States, as well as all underlying data for the trips on which those Incidents occurred.[48] Uber testified that the data it produced in response to the July 9, 2024 Order (and subsequent, related Orders) was exported from Uber's Bliss and Jira systems, and that Uber used a system called Flack to identify which data to export from Bliss and Jira.[49] Judge Cisneros issued an Order Resolving Discovery Letters Regarding Flack and S-RAD on October 3, 2025,[50] ordering Uber to produce data and documents related to SA/SM Incidents in the United States from the Flack System. I was granted access to the Bliss/Jira SA/SM Incident Data and the Flack SA/SM Incident Data via the AWS Secure Environment.[51]

19.1. **Bliss and Jira:** Uber testified that it exclusively used Bliss and Jira as the systems for recording and storing data related to reported SA/SM Incidents.[52] Bliss is a system Uber uses for customer support interaction, where Uber collects and stores information and data about SA/SM Incidents that are reported to Uber.[53] Jira is another software system that Uber uses for collecting data about SA/SM Incidents that are reported to Uber, but typically only the incidents Uber classifies as most serious (according to Uber's taxonomy) are included in Jira. The general process at Uber starting in 2017 was to enter reports of SA/SM Incidents (referred to

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[48] *In Re: Uber Technologies, Inc., Passenger Sexual Assault Litigation*, Case No. 23-md-03084-CRB. July 9, 2024 Order Granting in Part and Denying in Part Joint Discovery Letter Brief Regarding Discovery Related to Safety Data and Statistics.
[49] Deposition of Katherine McDonald, April 25, 2025, at 107-111 and Exhibits 653, 654, and 655 (McDonald Feb. 25, 2025 Certification).
[50] Docket No. 4060.
[51] *See* Updated Keller Report Appendix A for more details on the AWS Secure Environment.
[52] July 11, 2025 Deposition of Todd Gaddis at 88-90; April 25, 2025 Deposition of Katherine McDonald at 107-111; August 18, 2025 Declaration of T. Gaddis.
[53] McDonald Deposition April 24, 2025 #31489.1 p. 25-26; McDonald MDL Deposition p. 17-18.

by Uber as "tickets") into Bliss, and then enter a subset of those tickets into Jira.[54,55]

19.2. **Flack:** In addition to Bliss and Jira, Uber used a third system, Flack, to store and analyze data related to SA/SM Incidents. Uber described Flack as a "protected database" for housing data about SA/SM Incidents with permission restrictions that only allow certain Uber employees to perform queries.[56] The October 13, 2025 production of Flack SA/SM Incident Data was then amended on October 17, 2025, to include three additional fields, which I refer to as Uber's "Flack SA/SM Incident Data."[57] The data contained [redacted] The data included [redacted][58] from October 6, 2013[59] through December 31, 2024.

20. The April 9, 2025 production of Bliss/Jira SA/SM Incident Data consisted of the following four files. I refer to the data contained in these files in my report as Uber's "Bliss/Jira SA/SM Incident Data," which are:

20.1. **PROD_20250407_Jira_Ticket_Exports_UPDATED.csv ("Jira Tickets"):** The Jira Tickets data provides [redacted]. This file includes

[54] Deposition of Katherine McDonald 4/24/2025 at 18-46; Deposition of Katherine McDonald, 4/25/2025 at 109-110, 143-145.
[55] McDonald JCCP Deposition pg. 99; 89% of the Sexual Assault tickets recorded in Jira also have tickets in Bliss. However, there were 232 incidents that originated in Jira directly without a Bliss ticket, such as those reports from law enforcement and social media.
[56] Deposition of Katherine McDonald 4/24/2025 at 44; Deposition of Katherine McDonald, 4/25/2025 at 108-111.
[57] Uber's Flack system does not contain data for trips that were null for 'trip_uuid,' even though those same trips may be in the Bliss or Jira databases (*See* Deposition of Todd Gaddis 11/7/2025 at 75).
[58] Derived from the 'trip_request_time_local' field.
[59] See Footnote 2 regarding data prior to 2017 in the Flack SA/SM Incident Data.

data from the fields Uber identified as Jira fields,[60] including all fields identified in the certification from Katherine McDonald in January 2025.[61] This data included reports categorized as Sexual Assault or Sexual Misconduct with report tickets created between January 1, 2017, and December 31, 2022.[62]

20.2. **PROD_20250407_Jira_Comments_UPDATED.csv ("Jira Comments"):** This file includes data from the fields Uber identified in "Updated 3/24/2025 'Field Convenience Description' (Incident Report Field Convenience Descriptions 20250324 - Highly Confidential Attorneys' Eyes Only." [redacted].

20.3. **PROD_20250407_Bliss_Messages_UPDATED ("Bliss Messages"):** This file includes data from the fields Uber identified as Bliss fields,[63] and also includes all fields identified in the certification from Katherine McDonald in February 2025. [redacted]

20.4. **PROD_20250407_Bliss_Actions_UPDATED.csv ("Bliss Actions"):** This file includes data from the fields Uber identified as Bliss fields,[64] and also includes all fields identified in the declaration from Katherine McDonald in February 2025.[65] [redacted]

21. The Flack SA/SM Incident Data consisted of the following three files, all of which contain the same [redacted] across their respective years. I refer

[60] Deposition of Katherine McDonald 4/25/2025, Exhibit 658, p. 1-4.
[61] January 10, 2025 McDonald Certification.
[62] Derived from the 'created' field.
[63] Deposition of Katherine McDonald 4/25/2025, Exhibit 658, p. 1-4.
[64] Deposition of Katherine McDonald 4/25/2025, Exhibit 658, p. 1-4.
[65] February 25, 2025 McDonald Certification

to the data contained in these files in my report as Uber's "Flack SA/SM Incident Data," which are:

21.1. **Acp20172022flack.csv:** This file contained the incidents with a local trip request timestamp date from January 1, 2017 through December 31, 2022.

21.2. **Acp20232024flack.csv:** This file contained incidents with a local trip request timestamp date from January 1, 2023 through December 31, 2024.

21.3. **Acppre2017flack.csv:** This file contained incidents with a local trip request timestamp date from October 6, 2013 through December 31, 2016.

22. I outline the steps that I took to process and validate the Bliss/Jira SA/SM Incident Data and the Flack SA/SM Incident Data in this Updated Keller Report Appendix A.

iii. Data Dictionaries and Supplementary Files

23. **Data Dictionaries**: Uber provided multiple "data dictionaries" that list the fields that exist in Jira, Bliss, and Flack with descriptions that indicate how Uber used those fields.[66] Uber has also provided declarations confirming that Uber used those fields to collect and store information related to SA/SM Incident reports and that the field lists are accurate and complete.[67] I analyzed and interpreted the data in a manner consistent with the information provided by Uber in these data dictionaries.

V. Methodology

24. The methodology and steps I took to process and analyze the data that I used in this report are provided in Updated Keller Report Appendix A. I outline in detail the steps I took to load, transform, and clean the datasets that I analyze in this report. I document herein and in Updated Keller

[66] UBER_MDL3084_000378343; Updated March 24, 2025 "Field Convenience Description" (Incident Report Field Convenience Descriptions 20250324 - Highly Confidential Attorneys' Eyes Only.pdf; Deposition of Katherine McDonald 4/25/2025, Exhibits 656 and 658; August 18, 2025 Declaration of Todd Gaddis.

[67] Deposition of Katherine McDonald April 25, 2025 at 116 and Exhibits 654, 655; August 18, 2025 Declaration of Todd Gaddis.

Report Appendix A the inconsistencies that I found while processing these data sources.

25. Uber required that all Plaintiffs and their experts conduct any analysis of Uber's data in a secure virtual environment (AWS Secure Environment). More information about that system is detailed in Updated Keller Report Appendix A of this report. Any analysis I performed was done in the AWS Secure Environment.

26. I have disclosed the underlying code and methodology used in my analysis so that it is fully reproducible. The tools (e.g., Amazon Web Services, GitLab), coding languages (e.g., Python, SQL), and data processing techniques I used in this report are standard in the fields of Data Science and Data Analytics, and are widely recognized and accepted across the scientific and professional community. They were provisioned to me in a Secure Environment by a third-party contractor, BDO, agreed to by the Parties. A qualified expert could replicate my process and confirm the results; as such, the methodology is testable and reliable.

27. Because the data in this matter is confidential, subject to a Protective Order, and restricted to this litigation, my report (or any other relying upon such data) could not be published in peer-reviewed forums. However, the analytical methods and tools I applied are consistent with widely-accepted techniques that have been validated and published extensively in peer-reviewed literature, as discussed in Updated Keller Report Appendix A.

28. The procedures I used are based on direct and verifiable calculations. As such, a potential error rate or confidence interval is not applicable. I subjected my results to manual quality checks before including them in this report.

VI. Opinion 1: Uber's SA/SM Incident counts show hundreds of thousands of Sexual Assault and Sexual Misconduct incidents reported to Uber in the U.S. from 2017 through 2024

A. From 2017 through 2024, Uber received, classified into SA/SM Incident Subcategories, and retained in Flack 546,420 incidents of Sexual Assault and Sexual Misconduct.

29. Uber's Updated Flack Incident Report Classification Data showed that Uber received, classified into SA/SM Incident Subcategories, and retained in Flack 546,420 SA/SM Incidents from 2017 through 2024. The Flack SA/SM Incident Data and the Updated Flack Incident Report Classification Data completely aligned when comparing the monthly report volumes by Category and Subcategory for 2017 through 2024.

30. The following table shows the number of SA/SM Incidents reported and categorized by Uber in each year by each Category and Subcategory, according to the Updated Flack Incident Report Classification Data. This table also indicates whether Uber disclosed each Subcategory in its U.S. Safety Reports. This table includes SA/SM Incidents reports recorded and categorized by Uber against All Reported Parties.[68]

[68] "All Reported Parties" is in defined in Updated Keller Report Appendix B and refers to all SA/SM Incident reports made against Drivers, Riders, Third-Parties, or where the incident is considered Unknown (i.e., when the field carries a value of 'UNKNOWN', 'TAXI', or none of Uber's inferred fields identify a single, exclusive party).

Table 1: Number of Sexual Assault and Sexual Misconduct Incidents Per Subcategory Per Year (Source: Updated Flack Incident Report Classification Data, 2017-2024)

Category	Reported In Safety Report	2017	2018	2019	2020	2021	2022	2023	2024
Sexual Assault - Non-Consensual Sexual Penetration	Y	[redacted]							
Sexual Assault - Non-Consensual Kissing - Sexual Body Part	Y	[redacted]							
Sexual Assault - Non-Consensual Touching - Sexual Body Part	Y	[redacted]							
Sexual Assault - Attempted Non-Consensual Sexual Penetration	Y	[redacted]							
Sexual Assault - Non-Consensual Kissing - Non-Sexual Body Part	Y	[redacted]							
Sexual Assault - Non-Consensual Touching - Non-Sexual Body Part	N	[redacted]							
Sexual Assault - Attempted Kissing - Sexual Body Part	N	[redacted]							
Sexual Assault - Attempted Touching - Sexual Body Part	N	[redacted]							
Sexual Assault - Attempted Kissing - Non-Sexual Body Part	N	[redacted]							
Sexual Assault - Attempted Touching - Non-Sexual Body Part	N	[redacted]							
Sexual Assault - Insufficient Information	N	[redacted]							
Sexual Assault - Parent Category Usage Tracking	N	[redacted]							
Sexual Misconduct - Verbal Threat of Sexual Assault	N	[redacted]							
Sexual Misconduct - Masturbation/Indecent Exposure	N	[redacted]							
Sexual Misconduct - Masturbation	N	[redacted]							
Sexual Misconduct - Self Touching/Indecent Exposure	N	[redacted]							
Sexual Misconduct - Soliciting Sexual Act	N	[redacted]							
Sexual Misconduct - Indecent Photography/Videography Without Consent	N	[redacted]							
Sexual Misconduct - Displaying Indecent Material	N	[redacted]							
Sexual Misconduct - Comments or Gestures - Explicit Comments	N	[redacted]							
Sexual Misconduct - Comments or Gestures - Explicit Gestures	N	[redacted]							
Sexual Misconduct - Comments or Gestures - Flirting	N	[redacted]							
Sexual Misconduct - Comments or Gestures - Comments About Appearance	N	[redacted]							
Sexual Misconduct - Comments or Gestures - Asking Personal Questions	N	[redacted]							
Sexual Misconduct - Staring or Leering	N	[redacted]							
Sexual Misconduct - Insufficient Information	N	[redacted]							
Sexual Misconduct - Parent Category Usage Tracking	N	[redacted]							
TOTAL	-	71,080	93,464	99,201	41,360	34,790	52,933	70,530	83,062

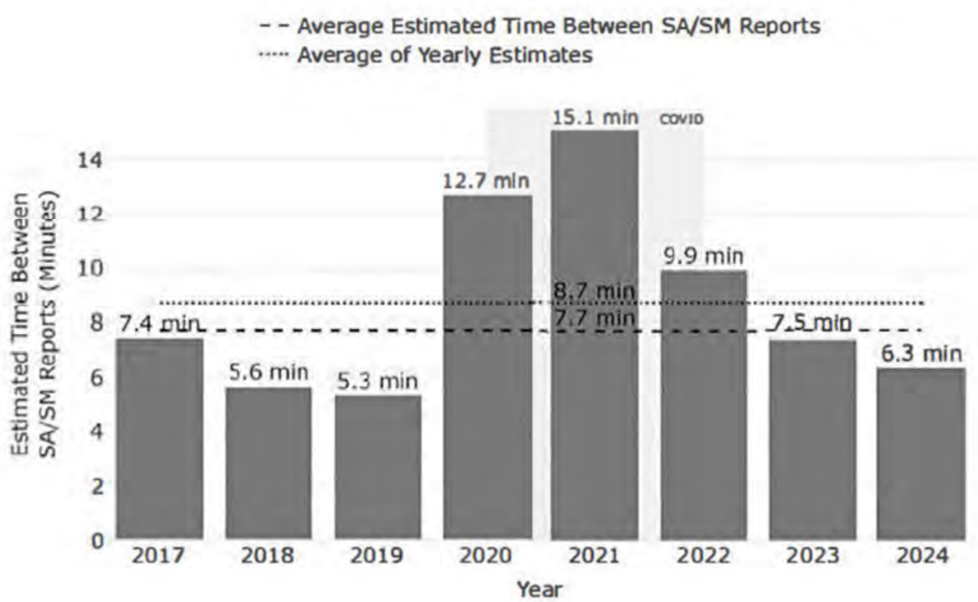
B. Between 2017 and 2024, a Sexual Assault or Sexual Misconduct Incident report was made to Uber the equivalent of every eight minutes.

31. From 2017 through 2024, an SA/SM Incident was reported to Uber the equivalent of every eight (7.7) minutes, according to the Updated Flack Incident Report Classification Data.[69] The estimated time between SA/SM Incidents was similar between 2017 and 2023, with the estimated time between SA/SM reports in 2017 being one every 7.4 minutes and one every 7.5 minutes in 2023. In 2024, SA/SM Incident reports were more frequent than in 2017 or 2023, with the estimated time between SA/SM Incident reports being one every 6.3 minutes.

[69] I calculate estimated time between SA/SM Incidents as follows: the total number of minutes between 2017 and 2024 divided by the number of SA/SM Incidents in the same time period, based off of Updated Flack Incident Report Classification Data.

32. The following figure shows the estimated time between SA/SM Incidents on an annual basis from 2017 through 2024, as well as two average calculations[70] across that same time interval, according to the Updated Flack Incident Report Classification Data. This figure includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties.

Figure 1: Estimated Time Between Sexual Assault and Sexual Misconduct Reports
(Source: Updated Flack Incident Report Classification Data, 2017-2024)



33. A Rape or Attempted Rape incident was reported to Uber the equivalent of every [redacted][71] [redacted].

[70] Averaging the annual estimated times as shown in the figure results in one SA/SM Incident reported to Uber every 8.7 minutes. Using estimated time calculations, the interval is every 7.7 minutes.

[71] I calculate estimated time between Rape and Attempted Rape as follows: the total number of minutes between 2017 and 2024 divided by the number of Rape and Attempted Rape incidents in the same time period, based off of Updated Flack Incident Report Classification Data.

34. The following figure shows the estimated time between Rape and Attempted Rape incidents on an annual basis from 2017 through 2024, as well as two average calculations[72] across that same time interval, according to the Updated Flack Incident Report Classification Data. This figure includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties.

Figure 2: Estimated Time Between Rape and Attempted Rape Reports
(Source: Updated Flack Incident Report Classification Data, 2017-2024)

[redacted]

[72] Averaging the annual estimated times as shown in the figure results in [redacted]

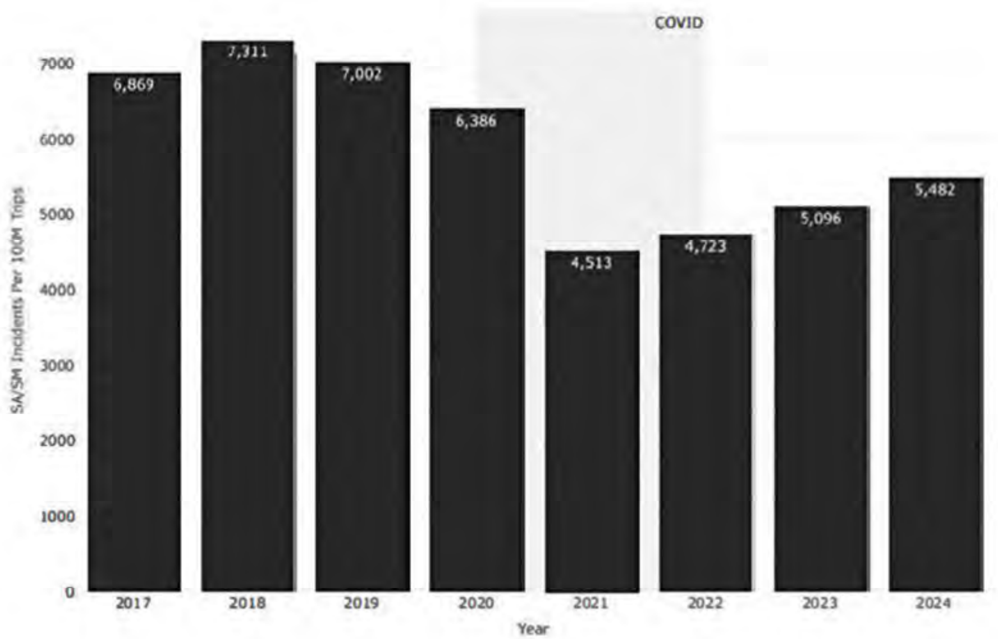
C. The number and rate of Sexual Assault and Sexual Misconduct Incidents reported to Uber have increased since 2021.

35. The number and rate[73] of SA/SM Incidents reported to Uber increased every year from 2021 through 2024, according to the Updated Flack Incident Report Classification Data. In 2023 and 2024, the SA/SM Incident rates per 100 million trips were 5,096 SA/SM Incidents and 5,482 SA/SM Incidents, respectively. From 2021 through 2024, the rate of SA/SM Incidents increased by 21.5% overall.

36. The following figure shows the rate of all SA/SM Incidents, calculated as the number of SA/SM Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes all SA/SM Incidents incident reports recorded and categorized by Uber against All Reported Parties, according to the Updated Flack Incident Report Classification Data.

[73] I calculate rate as follows: the number of SA/SM Incidents divided by the total number of Completed Rides Trips in the United States, multiplied by 100,000,000 to express the rate per 100 million completed trips. Uber also utilizes the same type of rate calculation in its U.S. Safety Reports. Wherever I refer to a rate, I refer to this calculation.

Figure 3: Rate of SA/SM Incidents Per Year
(Source: Updated Flack Incident Report Classification Data, 2017-2024)



37. [redacted].

38. The following figure shows the rate of SA/SM Incidents that Uber classified as Rape, calculated as the number of Rape Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes Rape incident reports recorded and categorized by Uber against All Reported Parties, according to the Updated Flack Incident Report Classification Data.

Figure 4: Rate of Rape Incidents Per Year
(Source: Updated Flack Incident Report Classification Data, 2017-2024)

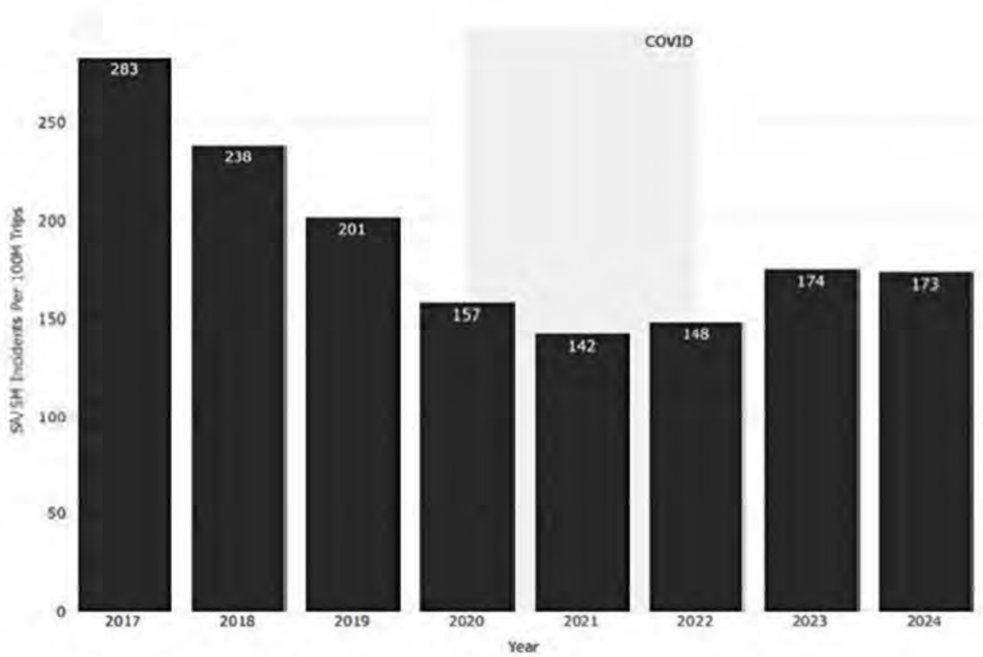
[redacted]

39. Since 2022, SA/SM Incident numbers have also increased within the Five Safety Report Subcategories[74] as a whole. Uber's 2021-2022 U.S. Safety Report disclosed a total of 1,080 SA/SM Incidents in 2021 and a total of 1,637 SA/SM Incidents in 2022.[75] For those same Five Safety Report Subcategories, [redacted] . [redacted] according to the Updated Flack Incident Report Classification Data.[76] In 2021 and 2022, the SA/SM Incident rate for the Five Safety Report Subcategories was 142 and 148 per 100 million trips, respectively, while rates for the same Five Safety Report Subcategories were [redacted] per 100 million trips in 2023 and 2024, respectively.

[74] Previously referred to as the "Publicly Disclosed Five" in my Opening Report.
[75] U.S. Safety Report 2021-2022, Table 7 p. 25.
[76] I calculate rate as follows: the number of SA/SM Incidents divided by the total number of Completed Rides Trips in the United States, multiplied by 100,000,000 to express the rate per 100 million completed trips. Uber also utilizes the same type of rate calculation in its U.S. Safety Reports. Wherever I refer to a rate, I refer to this calculation.

40. The following figure shows the rate of SA/SM Incidents that Uber classified in the Five Safety Report Subcategories, calculated as the number of SA/SM Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes SA/SM Incident reports recorded and categorized into the Five Safety Report Subcategories by Uber against All Reported Parties.

Figure 5: Rate of Five Safety Report Subcategories Incidents Per Year
(Source: Updated Flack Incident Report Classification Data, 2017-2024)



D. Uber acknowledges that Sexual Assault and Sexual Misconduct is underreported on its platform.

41. Uber has acknowledged that SA/SM Incidents are underreported nationwide,[77] citing in its 2017-2018 U.S. Safety Report a U.S. Department of Justice Study from September 2019 that found that only 25% of Sexual Assault or Rape incidents are reported to the police. Internally, Uber separately documented that it should assume that the SA/SM Incident reports received do not represent all of the SA/SM Incidents that occurred, and that actual numbers of SA/SM Incidents likely exceeded reported figures.[78] An Uber document from 2016 entitled "Sexual Assault and Rape Incident Rate Data Assumptions" states:

> "UBER only has data on incidents that are reported to us. It is likely and we should consider addressing that our numbers are lower than actual incidents due to underreporting – causes of which include fear for safety, intimidation, shame, etc. On our platform, many drivers have riders' home addresses, which alone could cause significant underreporting."

VII. Opinion 2: Uber's U.S. Safety Reports disclosed no more than 3.2% of Sexual Assault and Sexual Misconduct incident reports that Uber received, classified into SA/SM Incident Subcategories, and retained in Flack from 2017 through 2022 in the United States.

A. Uber excluded at least 96.8% of SA/SM Incidents from its U.S. Safety Reports.

42. Uber acknowledges that it has publicly disclosed 3% of the SA/SM Incidents reported to Uber from 2017 through 2022.[79] The following figure is an unedited screenshot from an August 6, 2025 Uber blog post.

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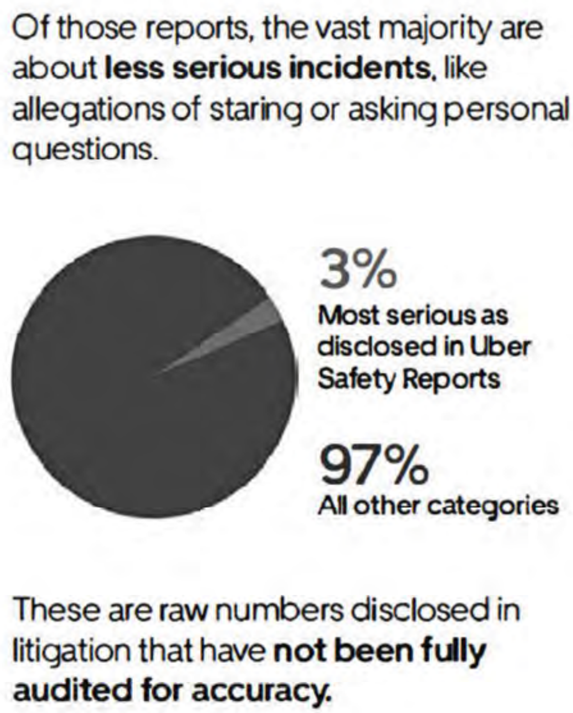
[77] 2017-2018 U.S. Safety Report, p.6; Deposition of Katherine McDonald, 4/24/2025, p. 235-236, p. 238-241; UBER000051856.
[78] UBER000051856.
[79] In response to an August 6, 2025 New York Times article, (https://www.nytimes.com/2025/08/06/business/uber-sexual-assault.html), Uber stated that the incidents it disclosed were limited to the "3% most serious." ("Uber's record on safety is clear." Uber Newsroom, https://www.uber.com/newsroom/ubers-safety-record/).

Figure 6: Percent of Sexual Assault and Sexual Misconduct Incidents That Uber Disclosed to the Public From 2017 Through 2022 (Source: Uber.com Blog Post: "Uber's record on safety is clear," August 6, 2025)



43. According to Uber's Updated Flack Incident Report Classification Data, Uber received, classified into SA/SM Incident Subcategories, and retained in Flack reports of 392,828 SA/SM Incidents from 2017 through 2022. In comparison, Uber's U.S. Safety Reports disclosed 12,522 reports (3.2%) during the same time period.[80] Uber has also tracked and classified 153,592 SA/SM Incidents from 2023 through 2024 that it has not disclosed in a Safety Report as of the date of this report. Including the SA/SM Incidents from 2023 through 2024, Uber has disclosed as of the

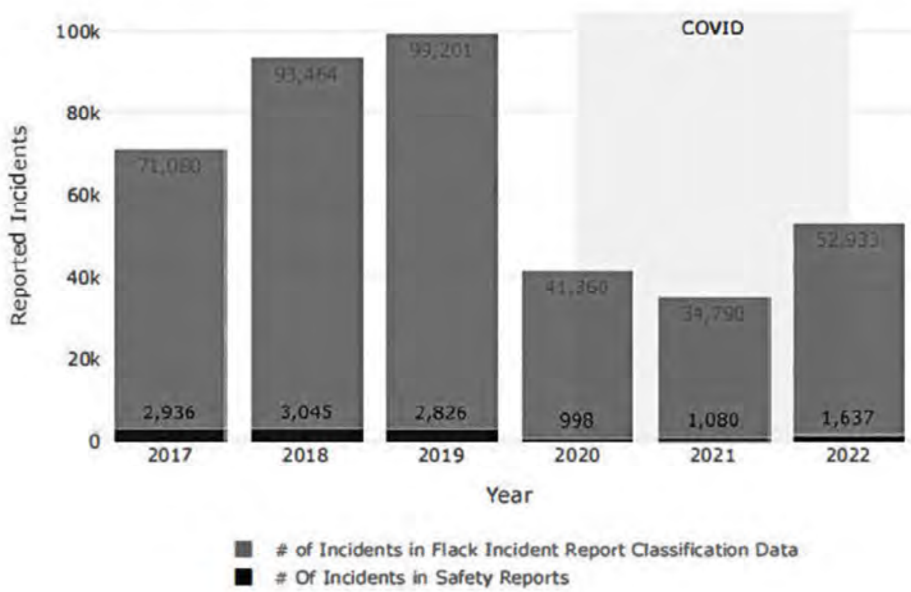
[80] U.S. Safety Report 2017-2018; U.S. Safety Report 2020-2021; U.S. Safety Report 2021-2022.

date of this report, no more than ￼2.3% of all SA/SM Incidents from 2017 through 2024.[81]

44. The following figure shows the difference between the number of SA/SM Incidents that Uber disclosed in its U.S. Safety Reports (blue) and the number of SA/SM Incidents based on Uber's Updated Flack Incident Report Classification Data (purple). Each bar is independent and should not be added together. In other words, the 71,080 SA/SM Incidents in the Updated Flack Incident Report Classification Data in 2017 should not be added to the 2,936 SA/SM Incidents reported in the U.S. Safety Report to obtain the total volume of SA/SM Incidents that year. This figure includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties.

[81] I identified SA/SM incident reports in the Bliss/Jira SA/SM Incident Data and Interrogatory No. 28 that were not in the Flack SA/SM Incident Data. Furthermore, I identified drivers that were in the Bliss/Jira SA/SM Incident Data and Interrogatory No. 16 and Interrogatory No. 29 that were not in the Flack SA/SM Incident Data. These may further impact this calculation. Please see Updated Keller Report Appendix A for more details.

Figure 7: Number of Sexual Assault and Sexual Misconduct Incident Reports That Uber Received Annually Compared to the Number Disclosed in Uber's U.S. Safety Reports
(Source: Updated Flack Incident Report Classification Data, 2017-2022; Uber's U.S. Safety Reports, 2017-2022)



45. The following table shows the difference between SA/SM Incidents that Uber disclosed in Uber's U.S. Safety Reports ("# Of Incidents in Uber U.S. Safety Reports (2017-2022)") and SA/SM Incidents reported to Uber ("# Of Incidents in The Updated Flack Incident Report Classification Data (2017-2024)"). Two separate total rows are displayed because Uber's U.S. Safety Reports covered years from 2017 through 2022, while the Updated Flack Incident Report Classification Data covered years from 2017 through 2024. This table includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties.

Table 2: Comparison Between Sexual Assault or Sexual Misconduct Incidents Uber Disclosed in U.S. Safety Reports and Sexual Assault or Sexual Misconduct Incidents Reported to Uber (Source: Updated Flack Incident Report Classification Data, 2017-2024; Uber's U.S. Safety Reports, 2017-2022)

Year	# Of Incidents In Ubers U.S. Safety Reports (2017-2022)	# Of Incidents In The Updated Flack Incident Report Classification Data (2017-2024)
2017	2,936	71,080
2018	3,045	93,464
2019	2,826	99,201
2020	998	41,360
2021	1,080	34,790
2022	1,637	52,933
2023		70,530
2024		83,062
TOTAL (2017-2022)	12,522	392,828
TOTAL (2017-2024)	-	546,420

B. Uber internally designated Subcategories of Sexual Assault and Sexual Misconduct Incidents as "Serious SA/SM"[82] but did not publicly disclose them.

46. In its U.S. Safety Reports, Uber publicly disclosed the number of SA/SM Incidents in the five Subcategories it referred to as the "most serious" (referred to in this report as the "Five Safety Report Subcategories").[83] However, internally, Uber referred to the following eight additional Subcategories[84] of SA/SM Incidents as "Serious SA/SM:"[85]

46.1. Sexual Assault - Non-Consensual Touching - Non-Sexual Body Part
46.2. Sexual Assault - Attempted Kissing - Sexual Body Part
46.3. Sexual Assault - Attempted Kissing - Non-Sexual Body Part
46.4. Sexual Assault - Attempted Touching - Sexual Body Part
46.5. Sexual Assault - Attempted Touching - Non-Sexual Body Part
46.6. Sexual Misconduct - Masturbation
46.7. Sexual Misconduct - Self Touching/Indecent Exposure
46.8. Sexual Misconduct - Verbal Threat of Sexual Assault

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[82] UBER_JCCP_MDL_001730535 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 52-67 and Exhibit 3103; Apr. 16, 2025 Deposition of Sunny Wong, p. 187-193 and Exhibit 2810-b; Apr. 2025 Deposition of Rebecca Payne, p. 93-98 and Exhibit 2508b); UBER_JCCP_MDL_000250826 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 92-95 and Exhibit 3108). I note that Ms. McDonald gives inconsistent testimony about the categorization of "indecent photography/videography without consent." I considered that Subcategory "non-serious" based on Ms. McDonald's testimony on p. 61 to 62 and 64 to 66, as well as Mr. Wong and Ms. Payne's corroborating testimony.

[83] Uber's U.S. Safety Reports 2017-2018, 2019-2020, 2021-2022.

[84] Uber's Flack system contains a field for [redacted] See UBER_JCCP_MDL_001102384 at 001102387.

[85] UBER_JCCP_MDL_001730535 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 52-67 and Exhibit 3103; Apr. 16, 2025 Deposition of Sunny Wong, p. 187-193 and Exhibit 2810-b; Apr. 2025 Deposition of Rebecca Payne, p. 93-98 and Exhibit 2508b); UBER_JCCP_MDL_000250826 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 92-95 and Exhibit 3108). I note that Ms. McDonald gives inconsistent testimony about the categorization of "indecent photography/videography without consent." I considered that Subcategory "non-serious" based on Ms. McDonald's testimony on p. 61 to 62 and 64 to 66, as well as Mr. Wong and Ms. Payne's corroborating testimony. The [redacted]

47. According to the Updated Flack Incident Report Classification Data, Uber received [redacted] reports in these eight "Serious SA/SM" Subcategories between 2017 and 2022. Uber received 12,590[86] incidents in the Five Safety Report Subcategories 2017 through 2022, for a combined total of [redacted][87] incidents that Uber retained in Flack and classified in one of the 13 "Serious SA/SM" Subcategories.

48. From 2017 to 2022, Uber categorized [redacted] "Serious SA/SM" incidents that it received and retained in Flack into the Five Safety Report Subcategories. Uber received an additional [redacted] reports in 2023 and [redacted] reports in 2024 of SA/SM Incidents that it classified into "Serious SA/SM" Subcategories, for a total of [redacted] incidents retained in Flack.[88] Overall, Uber categorized [redacted] of those Serious SA/SM Incidents into the Five Safety Report Subcategories. On an annual basis:[89]

48.1. **2017**: Uber categorized [redacted][90] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

48.2. **2018**: Uber categorized [redacted][91] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

[86] Updated Flack Incident Classification Data includes [redacted] SA/SM Incidents that occurred from 2017 through 2022 in the Five Safety Report Subcategories that were not included in Uber's U.S. Safety Reports (which disclosed 12,522 SA/SM Incidents). This total includes those [redacted] SA/SM Incidents.

[87] Ibid.

[88] Includes 5,022 SA Incidents Uber categorized into the Five Safety Report Subcategories.

[89] The percentages in this paragraph include the number of SA/SM Incidents Uber classified into these 13 Subcategories based on the Updated Flack Incident Classification Data, including [redacted] SA/SM Incidents Uber classified in the Five Safety Report Subcategories that were not included in Uber's U.S. Safety Reports (which disclosed 12,522 SA/SM Incidents).

[90] [redacted] more incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

[91] [redacted] more incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

48.3. **2019**: Uber categorized [redacted][92] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

48.4. **2020**: Uber categorized [redacted][93] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

48.5. **2021**: Uber categorized [redacted][94] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

48.6. **2022**: Uber categorized [redacted][95] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.

48.7. **2023**: Uber categorized [redacted] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.[96]

48.8. **2024**: Uber categorized [redacted] of all SA/SM Incident reports it classified as "Serious SA/SM" in the Updated Flack Incident Report Classification Data into the Five Safety Report Subcategories.[97]

48.9. **2025**: Uber has not published any 2025 data on SA/SM Incidents, nor did Uber provide 2025 data in the Updated Flack Incident Report Classification Data.

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[92] [redacted] fewer incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

[93] [redacted] fewer incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

[94] [redacted] fewer incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

[95] [redacted] fewer incidents were disclosed in the U.S. Safety Reports than were included in the Updated Flack Incident Classification Data that Uber considered to be part of the Five Safety Report Subcategories.

[96] Uber categorized [redacted] of all SA/SM Incidents it received and retained in Flack into Five Safety Report Subcategories.

[97] Uber categorized [redacted] of all SA/SM Incidents it received and retained in Flack into Five Safety Report Subcategories.

49. The following figure shows the proportion of the SA/SM Incidents that Uber classified into what Uber referred to as the five "most serious"[98] Subcategories, which were disclosed in Uber's U.S. Safety Reports (blue), relative to the SA/SM Incidents Uber classified into the 13 Subcategories that Uber referred to internally as "Serious SA/SM" (orange).[99] This figure includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties, according to the Updated Flack Incident Report Classification Data. Because Uber has not reported data for 2023 and 2024 as of the date of this report, those pie charts are shown in greyscale.

Figure 8: Proportion of Incidents Uber Classified as "Serious SA/SM" Relative to Five Safety Report Subcategories (Source: Updated Flack Incident Report Classification Data, 2017-2024)

[redacted]

Non-Safety Report Subcategory Serious SA/SM Incidents   Five Safety Report Subcategories

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[98] Uber's U.S. Safety Reports 2017-2018, 2019-2020, 2021-2022.
[99] UBER_JCCP_MDL_001730535 (Apr. 2, 2025 Deposition of Rebecca Payne, Exhibit 2508b; Apr. 24, 2025 Deposition of Katherine McDonald, Exhibit 3103); UBER_JCCP_MDL_000250826 (Apr. 24, 2025 Deposition of Katherine McDonald, Exhibit 3108).

50. Additionally, from 2017 through 2024, Uber received [redacted][00] SA/SM Incident reports that Uber classified in the following Subcategories,[101] which Uber considers to be "non-serious."[102] Uber does not disclose these incidents in its U.S. Safety Reports.[103]

50.1. Soliciting Sexual Act
50.2. Displaying Indecent Material
50.3. Explicit Comments
50.4. Explicit Gestures
50.5. Flirting
50.6. Comments about Appearance
50.7. Asking Personal Questions
50.8. Staring or Leering
50.9. Indecent Photography/Videography Without Consent

51. From 2017 through 2022, Uber received and retained in Flack [redacted] SA/SM Incident reports that it classified into the above nine undisclosed Sexual Misconduct Subcategories.[104]

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[100] This does not include SA/SM Incidents that Uber classified as "Insufficient Information" and "Parent Category Usage Tracking."
[101] As of my September 26, 2025 Expert Report, the data Uber had produced showed that Uber had received 409,623 SA/SM Incident reports that it did not consider "Serious SA/SM."
[102] UBER_JCCP_MDL_001730535 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 52-67 and Exhibit 3103; Apr. 16, 2025 Deposition of Sunny Wong, p. 187-193 and Exhibit 2810-b; Apr. 2, 2025 Deposition of Rebecca Payne, p. 93-98 and Exhibit 2508b); UBER_JCCP_MDL_000250826 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 92-95 and Exhibit 3108).
[103] Uber's 2017-2018 Safety Report at Appendix IV; Uber's 2019-2020 Safety Report at Appendix III.
[104] I recognize that the number of Subcategories in these subsections adds to 22 while Uber's Sexual Misconduct and Sexual Violence Taxonomy recognizes 21 Subcategories. This discrepancy exists because Uber has modified its Taxonomy over time. I analyzed the data as it was provided to me by Uber.

C. Uber categorized more than [redacted] Sexual Assault or Sexual Misconduct Incidents as Insufficient Information, a Subcategory that Uber did not disclose in Uber's U.S. Safety Reports.

52. From 2017 through 2022, Uber classified [redacted] SA/SM Incidents into the "Insufficient Information" Subcategory, based on Uber's conclusion that there were not enough details in the report to classify the incident into one of the 21 Subcategories of the taxonomy.[105] Uber did not disclose any SA/SM Incidents that it categorized as "Insufficient Information" in its Safety Reports. From 2023 through 2024, Uber classified an additional [redacted] SA/SM Incidents into the "Insufficient Information" Subcategory.

53. Additionally, from 2017 through 2021,[106] Uber classified [redacted] SA/SM Incidents into the "Parent Category Usage Tracking" Subcategory, based on Uber's conclusion that there were not enough details in the report to classify it into one of the 21 Subcategories of Uber's taxonomy.[107] Uber did not disclose the number of SA/SM Incidents that it categorized as "Parent Category Usage Tracking" in its Safety Reports.[108]

D. Uber received reports of Sexual Assault or Sexual Misconduct incidents that Uber categorized into the Five Safety Report Subcategories yet were not included in the totals disclosed in Uber's U.S. Safety Reports.

54. The Updated Flack Incident Report Classification Data shows that Uber received at least [redacted] reports[109] of SA/SM Incidents that were in the Five Safety Report Subcategories that Uber did not disclose in Uber's U.S. Safety Reports. [redacted].

[105] Deposition of Todd Gaddis, July 11, 2025, p. 78.
[106] It appears Uber discontinued use of this designation in 2021.
[107] Deposition of Todd Gaddis, July 11, 2025, p. 82.
[108] From 2023 through 2024, Uber did not classify any additional SA/SM Incidents into the "Parent Category Usage Tracking" Subcategory.
[109] For 2017 and 2018, the Safety Report disclosed [redacted] more incidents than were calculated by Uber in the Updated Flack Incident Data. For 2019 and 2020, the Safety Report disclosed [redacted] fewer incidents than were calculated by Uber in the Updated Flack Incident Data. For 2021 and 2022, the Safety Report disclosed [redacted] fewer incidents than were calculated by Uber in the Updated Flack Incident Report Classification Data.

VIII. Opinion 3: Uber internally discussed that there were "precursors"[110] to Sexual Assault and Sexual Misconduct Incidents, but it did not disclose that information in U.S. Safety Reports.[111]

A. Uber's internal analyses documented that trips during late-night hours on weekends were "high risk"[112] for Sexual Assault and Sexual Misconduct Incidents.

55. Uber's internal documents indicate that the day of the week and time of day of a trip are correlates for SA/SM Incidents, and that trips during night hours and on weekends are correlated with higher rates of SA/SM Incidents.[113] Some internal Uber analyses that predate the first U.S. Safety Report document that [redacted][114] and that [redacted][115]

56. One analysis showed that [redacted][116] Another analysis indicated that [redacted] were reported on trips that were completed between 10 P.M. and 6 A.M. on weekends, although 10% of overall Uber trips occurred during these hours.[117] On average during the week, Uber's internal analysis documented that a disproportionate volume of Rape incidents occurred during late-night hours from Friday nights through Sunday mornings.[118]

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[110] UBER_JCCP_MDL_000356814.
[111] Based on my review of the Flack fields list in Todd Gaddis's August 18, 2015 declaration and my review of documents and testimony in this case, it is my opinion that Uber maintains data sufficient to analyze these trends and patterns; however, as of the date of this report, Uber still has not produced this information, including as part of its Flack productions.
[112] UBER_JCCP_MDL_001687315.
[113] UBER_JCCP_MDL_003504225; UBER_JCCP_MDL_000356814; UBER_JCCP_MDL_001755017; UBER_JCCP_MDL_000031720.
[114] UBER000204698; UBER_JCCP_MDL_001755017.
[115] UBER_JCCP_MDL_003504225, p. 7.
[116] UBER_JCCP_MDL_000258366.
[117] UBER_JCCP_MDL_002249692.
[118] UBER_JCCP_MDL_000031720.0007.

B. Prior to the publication of any U.S. Safety Reports, Uber identified male Drivers and female Riders as well as the proximity of a pick-up to a bar as "precursors"[119] to Sexual Assault and Sexual Misconduct.

57. Uber's analysis of its own SA/SM Incident reports showed that pairings between opposite gender Riders and Drivers and the proximity of the pickup location to a bar were correlated with Sexual Assault and Sexual Misconduct.[120] Uber's data showed that SA/SM Incidents were more likely to be reported against men, with [redacted][121] For Rape incidents specifically, Uber's data showed that reports were [redacted][122] Uber's internal analysis showed that [redacted].[123] Uber did not produce gender or inferred gender data nor GPS data in this litigation.

58. The following figures are Uber-produced documents for this litigation and are unedited from the original productions.

[119] UBER_JCCP_MDL_000356814.
[120] UBER_JCCP_MDL_000031720.
[121] UBER_JCCP_MDL_000031720.0008.
[122] UBER_JCCP_MDL_000031720.0008.
[123] UBER_JCCP_MDL_003306684.

Figure 9: Internal Uber Presentations Showed That Pick-Ups Within 50 Meters of a Bar Were Correlated with Higher Sexual Assault Rates (Source: UBER_JCCP_MDL_000031720.0009)

[redacted]

Figure 10: Internal Uber Presentations Show Male-Driver and Female-Rider Pairings Were Correlated with Higher Sexual Assault Rates
(Source: UBER_JCCP_MDL_000031720.0008)

[redacted]

IX. Opinion 4: Uber tracked in Flack which of its Drivers had prior SA/SM Incidents and internally discussed that having a prior SA/SM Incident made a Driver more likely to be reported for SA/SM again.

A. Uber's internal analyses showed that Drivers with previous Sexual Assault and Sexual Misconduct incidents were more likely to be reported for SA/SM again.[124]

59. Uber has identified a history of prior SA/SM Incidents as a "pattern" related to future SA/SM Incidents.[125] In July 2017, Uber's internal analyses showed that [redacted][126] Additionally, Drivers with previous SA/SM Incident reports were more likely to have "patterns of escalation,"[127] meaning a more serious SA/SM Incident (according to Uber's taxonomy) in the future.

60. Uber also analyzed the relationship between Drivers' "feedback tags" and SA/SM Incidents.[128] As shown in the following image, [redacted][129] Uber did not disclose this information in its Safety Reports, nor produce data on Feedback Tags received by all Drivers involved in SA/SM Incidents.

61. The following excerpted figure is from an Uber-produced document for this litigation and is unedited from its original production.

[124] UBER_JCCP_MDL_000031720.
[125] UBER_JCCP_MDL_000964270.
[126] UBER_JCCP_MDL_001687315; June 25, 2025 Deposition of Sunny Wong at 208-209; June 17, 2025 Deposition of Greg Brown at 32-39. Uber did not provide the data to perform this analysis independently.
[127] UBER_JCCP_MDL_000014232.
[128] When a Rider rates a Driver less than five stars, the Rider is then offered certain tags to select if they want to provide more information regarding the rating. *See* April 18, 2025 Deposition Valerie Shuping at 369.
[129] August 25, 2025 Deposition of Greg Brown, Exhibit 1932.

Figure 11: Internal Uber Presentations Show Certain Feedback Tags Were Correlates of Sexual Assault and Sexual Misconduct Incidents (Source: August 25, 2025 Deposition of Greg Brown, Exhibit 1932)

[redacted]

62. Uber corporate witness Elizabeth Ross testified that Uber has a responsibility to take steps to try to deter SA/SM Incidents.[130] Uber corporate witness Rebecca Payne testified that it is important to "deactivate" Drivers who are reported for Sexual Assault from the Uber platform so they can no longer drive for Uber.[131] Uber corporate witness Heather Childs testified that Drivers who have been reported for Sexual Assault should be deactivated immediately.[132] Uber internally assessed that, [redacted][133] In its 2017-2018 U.S. Safety Report, Uber stated "*When we receive a report of sexual assault, we immediately remove the accused party's access to the Uber app while support agents complete a review*," as shown in the figure below.

[130] June 12, 2025 Deposition of Elizabeth Ross at 394-395..
[131] May 12, 2025 Deposition of Rebecca Payne at 559.
[132] June 5, 2025 Deposition of Heather Childs at 27.
[133] May 20, 2025 Deposition of Michael Akamine, at 418-420 and Exhibit 890.

Figure 12: Uber Safety Report Excerpt
(Source: U.S. Safety Report 2017-2018)[134]

> When we receive a report of sexual assault, we immediately remove the accused party's access to the Uber app while support agents complete a review.

63. In the same report, Uber stated: "Uber will ban users from the platform if we are able to obtain a statement of experience from the survivor and/or obtain relevant facts (e.g., GPS data, timestamps, videos/photos, in-app communications). We adhere to this standard for all sexual assault categories described in this report."[135] They further clarify in a footnote in the 2017-2018 U.S. Safety Report that a subset of Sexual Misconduct Subcategories were also included: "Similar protocols are followed for the following urgent categories of sexual misconduct: Indecent Photography/Video Without Consent, Masturbation/Indecent Exposure, and Verbal Threat of Sexual Assault."

64. The list of Drivers that Uber identified as 1) having been reported for an SA/SM Incident from January 1, 2017 through December 31, 2022, and 2) subsequently deactivated during that time period for any reason (including reasons unrelated to the SA/SM Incident for which the Driver was reported) contains 207,058 Drivers as was provided as part of Interrogatory No. 16/29 and the Interrogatory No. 16/29 Addendum. In contrast, Uber received, classified into SA/SM Categories, and retained in Flack 392,828 SA/SM Incident reports for trips occurring from January 1, 2017 through December 31, 2022.

[134] Uber's U.S. Safety Report 2017-2018, p. 12.
[135] Uber's U.S. Safety Report 2017-2018, p. 12-13.

B. Approximately [redacted] SA/SM Incidents reported against Uber Drivers involved Drivers who had already been reported once to Uber for SA/SM.

65. From 2017 through 2024, Uber Drivers who had already been reported once to Uber for SA/SM were responsible for [redacted] of all SA/SM Incidents reported against Drivers on the platform , according to Uber's Flack SA/SM Incident Data. Nearly [redacted] Uber Drivers with a SA/SM Incident reported against them were reported for another incident of the same Subcategory, or a more serious one, within one year of a previously reported SA/SM Incident. Nearly [redacted] Drivers with SA/SM Incidents reported against them were reported for another incident within four months of a previous report against them.

66. The figure below presents the volume of Uber trips with SA/SM Incident reports against Drivers from 2017 through 2024, distinguishing between trips involving Drivers with a single SA/SM Incident report (orange) and those with one or more prior SA/SM Incident reports (purple). The following figure then displays the percentage of Uber trips with SA/SM Incident reports that were from Drivers with one or more prior SA/SM Incident reports for the same time period, according to Uber's Flack SA/SM Incident Data.

Figure 13: SA/SM Incidents Involving Drivers Who Had Already Been Reported to Uber for SA/SM Compared to Total SA/SM Incident Reports[136]
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

[136] "Trips with Reports Against Drivers With No Prior Reports Against Them" also includes 622 trips where no Driver UUID ([redacted]") was entered by Uber.

Figure 14: Percent of SA/SM Incidents Per Year Involving Drivers Who Had Already Been Reported to Uber for SA/SM
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

67. [redacted] of trips where a Rape or Attempted Rape was reported to Uber involved Drivers who had previously been reported to Uber for an SA/SM Incident resulting from trips from 2017 through 2024. Reports concerning [redacted] involved the highest percentage of drivers with a prior SA/SM Incident reports, with [redacted] of incidents originating from drivers with a prior SA/SM Incident report resulting from trips from 2017 through 2024.

68. The table below presents the volume of SA/SM reports by Subcategory, alongside the number of unique Drivers who were reported for each Subcategory. For each Subcategory, the table also shows the number and percentage of SA/SM Incident reports that involved Drivers who had at least one prior SA/SM Incident reported against them to Uber. The table only considers Drivers with SA/SM Incidents reported on trips occurring between 2017 through 2024. Because a single Driver may have multiple SA/SM Incident reports in different Subcategories, "Number of Drivers With Reports" should not be summed across rows.

Table 3: Percent of Trips by Subcategory with SA/SM Reports Among Drivers With At Least One Prior SA/SM Report
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

69. Among Drivers who were reported at least once for Rape or Attempted Rape, and had other prior reports against them before the for Rape or Attempted Rape report on trips occuring from 2017 through 2024, [redacted]

70. The following figure is limited to Drivers with prior SA/SM Incidents occurring on trips from 2017 through 2024. The pie shows the breakdown of Subcategories of prior reports against Drivers who were later reported for Rape or Attempted Rape, respectively.

Figure 15: Prior SA/SM Incident Subcategories for Drivers Who Were Later Reported for Rape or Attempted Rape (Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

X. Opinion 5: Uber's Flack System includes specific columns and fields for data on auditing, reporting parties (i.e., Drivers, Riders), the time and day of SA/SM Incident reports, and city-level information.

A. Uber audited a vast majority [redacted] of the 546,420 trips retained in Flack that had SA/SM Incidents.

71. Uber has published that audits are conducted internally for the purpose of "auditor alignment"[137] for trips disclosed in the U.S. Safety Reports and also testified that there is a separate audit for the purpose of inclusion in the U.S. Safety Reports.[138] On August 6, 2025, Uber published a blog on its Newsroom that referenced the Subcategories of SA/SM that the company does not disclose in its U.S. Safety Reports, stating: "*most of the approximately 400,000 reports are unaudited, meaning they haven't gone through the same rigorous vetting process as the data included in*

[137] From the Uber 2019-2020 U.S. Safety Report: "Uber aims to ensure that the categories of sexual assault included in this report have at least 85% of auditor classification alignment with internal safety taxonomy experts."
[138] Deposition of Todd Gaddis, November 7, 2025 at 114.

our Safety Reports."[139] In every year from 2017 through 2024, Uber audited at every Subcategory level a vast majority ([redacted]) of the 546,420 trips that had SA/SM Incidents.[140] Uber audited over [redacted] of trips where a Sexual Assault was reported, and over [redacted] of trips where Sexual Misconduct was reported, according to Uber's Flack SA/SM Incident Data for 2017 through 2024. Specifically, four Sexual Misconduct Subcategories, specifically "Verbal Threat of Sexual Assault," "Indecent Photography/Videography Without Consent," "Displaying Indecent Material," and "Comments or Gestures - Explicit Gestures," were [redacted] audited in at least one year in the data period.

72. The following table shows the percentage of Uber trips that Uber's Flack SA/SM Incident Data shows as audited,[141] by year and SA/SM Subcategory, for SA/SM Incidents reported on trips occurring from 2017 through 2024. This table includes SA/SM Incident reports recorded and categorized by Uber against All Reported Parties. The highlighted rows represent Incident Subcategories included in the Five Safety Report Subcategories.

[139] Nilles, Hannah. "Uber's Record on Safety Is Clear." Uber Newsroom, 6 Aug. 2025, www.uber.com/newsroom/ubers-safety-record/.
[140] This refers to Subcategories other than Insufficient information and Parent Category Usage Tracking, although Insufficient Information still shows that a majority of trips were audited
[141] Where [redacted]

[redacted]

73. The following table shows the percentage of Uber trips in each Subcategory that Uber's Flack SA/SM Incident Data shows as audited,[143] grouped by the years in which Uber published each Safety Report. Although the Flack SA/SM Incident Data included trips requested for years 2013 through 2024, this table is limited to years when Uber published U.S. Safety Reports (2017-2022) and only includes reports that were reported to Uber by the date of each safety report's publication.[144] This table includes SA/SM Incidents reports recorded and categorized by Uber against All Reported Parties.

[142] 0.00%% values in the table indicate null values
[143] Where [redacted]
[144] *See* Footnote 3.

Table 5: Percent of Trips Uber Audited By Safety Report Publication Date[145]
(Source: Flack SA/SM Incident Data, 2017-2022)

[redacted]

B. 432,638 SA/SM Incidents were reported to Uber against Uber Drivers from 2017 to 2024.

74. Uber's internal SA/SM Incident counts showed that 432,638 SA/SM Incidents were reported to Uber against Uber Drivers from 2017 through 2024, according to Uber's Flack SA/SM Incident Data.

75. The following table shows the number of SA/SM Incidents reported to Uber against Uber Drivers each year shown by Subcategory, according to the Flack SA/SM Incident Data. This table also indicates with a Y/N column whether Uber disclosed each Subcategory in its U.S. Safety Reports. This table includes only SA/SM Incidents reported against Drivers on trips occurring from 2017 through 2024.

[145] *See* Footnote 3.

Table 6: Annual Number of Sexual Assault and Sexual Misconduct Incidents Reported Against Drivers Per Subcategory Per Year (Source: Flack SA/SM Incident Data, 2017-2024)

Category	Reported In Safety Report	2017	2018	2019	2020	2021	2022	2023	2024
Sexual Assault - Non-Consensual Sexual Penetration	Y	[redacted]							
Sexual Assault - Non-Consensual Kissing - Sexual Body Part	Y								
Sexual Assault - Non-Consensual Touching - Sexual Body Part	Y								
Sexual Assault - Attempted Non-Consensual Sexual Penetration	Y								
Sexual Assault - Non-Consensual Kissing - Non-Sexual Body Part	Y								
Sexual Assault - Non-Consensual Touching - Non-Sexual Body Part	N								
Sexual Assault - Attempted Kissing - Sexual Body Part	N								
Sexual Assault - Attempted Touching - Sexual Body Part	N								
Sexual Assault - Attempted Kissing - Non-Sexual Body Part	N								
Sexual Assault - Attempted Touching - Non-Sexual Body Part	N								
Sexual Assault - Insufficient Information	N								
Sexual Assault - Parent Category Usage Tracking	N								
Sexual Misconduct - Verbal Threat of Sexual Assault	N								
Sexual Misconduct - Masturbation	N								
Sexual Misconduct - Self Touching/Indecent Exposure	N								
Sexual Misconduct - Soliciting Sexual Act	N								
Sexual Misconduct - Indecent Photography/Videography Without Consent	N								
Sexual Misconduct - Displaying Indecent Material	N								
Sexual Misconduct - Comments or Gestures - Explicit Comments	N								
Sexual Misconduct - Comments or Gestures - Explicit Gestures	N								
Sexual Misconduct - Comments or Gestures - Flirting	N								
Sexual Misconduct - Comments or Gestures - Comments About Appearance	N								
Sexual Misconduct - Comments or Gestures - Asking Personal Questions	N								
Sexual Misconduct - Staring or Leering	N								
Sexual Misconduct - Insufficient Information	N								
Sexual Misconduct - Parent Category Usage Tracking	N								
TOTAL	-	52,218	72,205	78,669	33,576	27,172	43,886	57,415	67,497

C. Between 2017 and 2024, a Sexual Assault or Sexual Misconduct Incident report was made to Uber against an Uber Driver the equivalent of every ten minutes.[146]

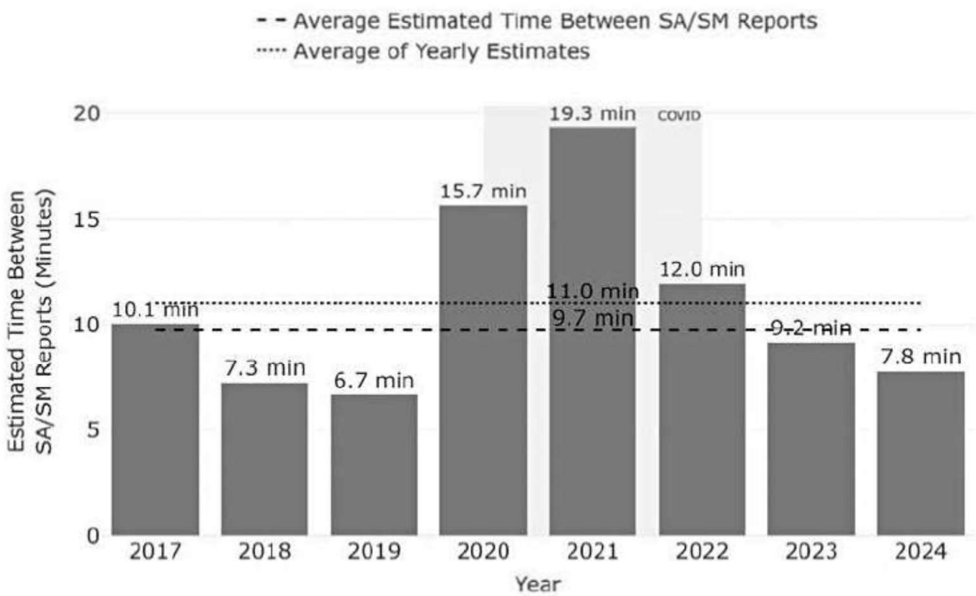
76. From 2017 through 2024, an SA/SM Incident was reported against an Uber Driver the equivalent of every ten (9.7) minutes.[147] SA/SM Incidents were reported against Drivers most frequently in 2018 and 2019, and again in 2024. The estimated time between SA/SM Incident reports in 2018 was one every 7.3 minutes; in 2019, every 6.7 minutes; and in 2024, every 7.8 minutes.

[146] I calculate estimated time between SA/SM Incidents as follows: the total number of minutes between 2017 and 2024 divided by the number of SA/SM Incidents in the same time period, based on Flack Incident Report Classification Data.

[147] Averaging the annual estimated times shown in the figure results in one SA/SM Incident reported to Uber every 11.0 minutes. Calculating estimated time results in an interval of every 9.7 minutes.

77. The following figure shows the estimated time between SA/SM Incidents reported against Uber Drivers on an annual basis from 2017 through 2024 as well as two average calculations[148] across that same time interval, according to Uber's Flack SA/SM Incident Data. This figure includes only SA/SM Incidents reported against Drivers.

Figure 16: Annual Average Frequency of Sexual Assault and Sexual Misconduct Incidents Reported Against Drivers Per Year in Minutes (Source: Flack SA/SM Incident Data, 2017-2024)



78. From 2017 to 2024, Uber received the equivalent of one Rape or Attempted Rape incident report every [redacted], meaning approximately one report of Rape or Attempted Rape against an Uber Driver [redacted] from 2017 through 2024.

79. The following figure shows the estimated time between Rape and Attempted Rape incident reports made to Uber against Uber Drivers on an annual basis from 2017 through 2024 as well as two average

[148] Averaging the annual estimated times as shown in the figure results in one SA/SM Incident reported to Uber every 11.0 minutes. Using estimated time calculations, the interval is every 9.7 minutes.

calculations[149] across that same time interval, according to Uber's Flack SA/SM Incident Data. This figure includes only SA/SM Incidents reported against Drivers.

Figure 17: Estimated Time Between Rape or Attempted Rape Reports Against Drivers in Hours
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

[149] Averaging the annual estimated times as shown in the figure results in one SA/SM Incident reported to Uber every [redacted]. Using estimated time calculations, the interval is every [redacted].

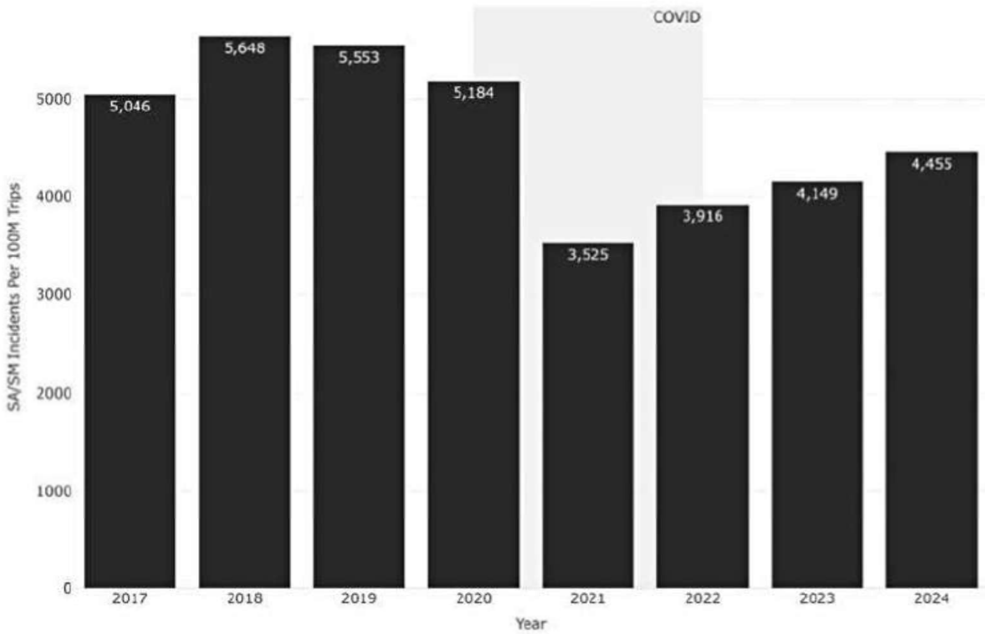
D. The number and rate of Sexual Assault and Sexual Misconduct Incidents reported to Uber against Uber Drivers has increased since 2021.

80. The number and rate[150] of SA/SM Incidents reported against Drivers increased year-over-year every year from 2021 through 2024. In 2023 and 2024, SA/SM Incident rates per 100 million trips were 4,149 SA/SM Incidents and 4,455 SA/SM Incidents, respectively.

81. The following figure shows the rate of all SA/SM Incidents, calculated as the number of SA/SM Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes all SA/SM Incident reports recorded and categorized by Uber against Drivers, according to the Flack SA/SM Incident Data.

[150] I calculate "rate" as follows: the number of Sexual Assault and Sexual Misconduct (SA/SM) incidents divided by the total number of Completed Rides Trips in the United States, multiplied by 100,000,000 to express the rate per 100 million completed trips. Uber also utilizes the same type of rate calculation in its U.S. Safety Reports. Wherever I use the term "rate," I refer to this calculation.

Figure 18: Annual Rate of SA/SM Incidents Reported Against Drivers Per Year (Source: Flack SA/SM Incident Data, 2017-2024)



82. [redacted], according to Uber's Flack SA/SM Incident Data. Reports of Rape were at a rate of [redacted] per 100 million trips in 2017, compared to [redacted] per 100 million trips in 2023 and to [redacted] per 100 million trips in 2024.

83. The following figure shows the rate of SA/SM Incidents reported to Uber against Uber Drivers that Uber classified as Rape, calculated as the number of Rape Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes only Rape Incidents reported against Drivers.

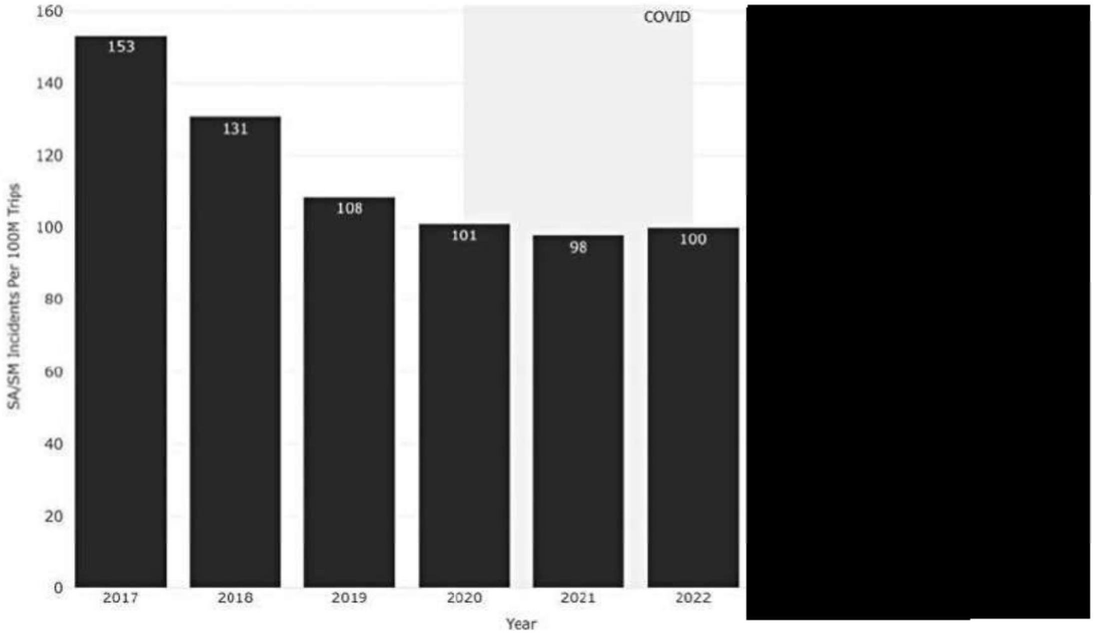
Figure 19: Annual Rate of Rape Incidents Reported Against Drivers Per Year (Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

84. Since 2021, SA/SM Incidents reported against Uber Drivers have also [redacted]

85. The following figure shows the rate of SA/SM Incidents reported to Uber against Uber Drivers that Uber classified in the Five Safety Report Subcategories, calculated as the number of SA/SM Incidents divided by the total number of completed Uber trips multiplied by 100 million. This figure includes only SA/SM Incidents reported against Drivers.

Figure 20: Annual Rate of SA/SM Incidents in the Five Safety Report Subcategories Reported Against Drivers Per Year (Source: Flack SA/SM Incident Data, 2017-2024)



86. The following figure shows the proportion of SA/SM Incidents reported against Drivers that Uber classified into the Five Safety Report Subcategories (blue), relative to the SA/SM Incidents Uber classified into the 13 Subcategories that Uber referred to internally as "Serious SA/SM" (orange). This figure includes only SA/SM Incidents reported against Drivers. Because Uber has not reported data for 2023 and 2024 as of the date of this report, those pie charts are shown in greyscale.

Figure 21: Proportion of Incidents Reported Against Drivers Uber Classified as "Serious SA/SM" Relative to Five Safety Report Subcategories
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

E. According to the Flack SA/SM Incident Data for 2017-2024, [redacted] of SA/SM Incidents in the Five Safety Report Subcategories were reported against Riders; however, [redacted] of Rape and Attempted Rape incidents were reported against Drivers.

87. Uber's U.S. Safety Report 2017-2018 stated that 54% of SA/SM Incidents in the Five Safety Report Subcategories were reported to Uber against Drivers, while 45% were reported to Uber against Riders.[151] In the 2019-2020 U.S. Safety Reports, Uber published that "nearly half" of all SA/SM Incidents in the Five Safety Report Subcategories were reported against Riders, at 43%.[152]

88. The following table shows the number of unique Uber trips with SA/SM reports and the percentage of those trips that were reported against Drivers and Riders,[153] respectively, according to Uber's Flack SA/SM Incident Data.

[151] https://tb-static.uber.com/prod/udam-assets/drclg/UberUSSafetyReport_201718_FullReport.pdf.

[152] Uber 2019-2020 U.S. Safety Report.

[153] Across all years, < 0.2% of incidents were reported against Third and unknown parties.There were 109,229 unique [redacted]" values that made reports against Riders from 2017 through 2024.

Table 7: Percent of All SA/SM Incidents Against Drivers and Riders By Year
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

89. The following table shows the number of unique Uber trips with SA/SM reports in the Five Safety Report Subcategories and the percentage of those trips that were reported against Drivers and Riders, respectively.[154] The highlighted rows represent years of data (2023, 2024) that Uber has not disclosed to the public as of the date of this report.

[154] Across all years, [redacted] were reported against Third and unknown parties.

Table 8: Percent of SA/SM Incidents in the Five Safety Report Subcategories Against Drivers and Riders By Year (Source: Flack SA/SM Incident Data, 2017-2024)

Year	Number Of Trips With Reports	% Of Trips With Reports Against Driver	% Of Trips With Reports Against Rider
2017	2,928	54.2%	45.1%
2018	3,041	55.0%	44.5%
2019	2,850	53.9%	45.4%
2020	1,020	64.1%	34.9%
2021	1,091	69.0%	29.8%
2022	1,660	67.5%	31.4%
[redacted]	[redacted]	[redacted]	[redacted]
[redacted]	[redacted]	[redacted]	[redacted]

90. In every year from 2017 to 2024, between [redacted] of trips with Rape and Attempted Rape reports were reported against Drivers. The highest percentage occurred in 2023, when [redacted] of reported Rape and Attempted Rape incidents were against Drivers.

91. The following table shows the number of unique Uber trips with Rape and Attempted Rape reports and the percentage of those trips that were reported against Drivers and Riders, respectively, according to Uber's Flack SA/SM Incident Data.[155]

[155] Across all years, [redacted] incidents were reported against Third and unknown parties.

Table 9: Percent of Rape and Attempted Rape Incidents Against Drivers and Riders By Year
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

92. Certain Subcategories had a majority of reports against Drivers, while others had a majority of reports against Riders. Four Subcategories had reports where [redacted] of reports made to Uber were about Drivers. These were "Comments or Gestures - Flirting", "Comments or Gestures - Comments About Appearance", "Comments or Gestures - Asking Personal Questions", and "Staring or Leering", and totaled [redacted] trips reported to Uber about Drivers. Five Subcategories contained [redacted] of the reports against Riders: "Non-Consensual Kissing - Non-Sexual Body Part," "Non-Consensual Touching - Non-Sexual Body Part," "Attempted Kissing - Non-Sexual Body Part," "Masturbation," and "Self Touching/Indecent Exposure". Together, these constituted [redacted] reports against Riders.

93. The following table shows the number of unique Uber trips with SA/SM reports and the percentage of those trips that were reported against Drivers and Riders, respectively, shown by Category and Subcategory, according to Uber's Flack SA/SM Incident Data from 2017 through 2024.[156]

[156] For all Subcategories, [redacted] of incidents were reported against Third and unknown parties.

Table 10: Percent of SA/SM Incidents Reported Against Drivers and Riders By Subcategory
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

F. More SA/SM Incidents occurred on late nights and weekends.

94. Uber does not disclose the frequency of SA/SM Incident reports by time of day in its U.S. Safety Reports. Although Weekend Late Nights constitutes [redacted] the hours in the week,[157] [redacted] of Rape or Attempted Rape incidents reported against Drivers occured on trips during that time. Furthermore, [redacted] of trips with reported SA/SM Incidents in the Five Safety Report Subcategories against Drivers occurred during Weekend Late Nights. When comparing the same Late Night hours (12:00–4:59 a.m.) on Weekdays ("Weekday Late Nights") and Weekends ("Weekend Late Nights"), SA/SM Incident reports against Drivers occurred at higher rates on weekends. Overall, SA/SM Incidents were approximately [redacted] during Weekend Late Nights compared to Weekday Late Nights. SA/SM Incidents in the Five Safety Report Subcategories were [redacted] more frequent, and reports of Rape and Attempted Rape were [redacted] more frequent during Weekend Late Nights than during the same hours on weekdays.

95. The following figures show the distribution of trips with SA/SM Incident reports by hour of the day and day of the week for all SA/SM Subcategories, the Five Safety Report Subcategories, and Rape and Attempted Rape, respectively, according to Uber's Flack SA/SM Incident Data from 2017 through 2024. All three figures include only trips with SA/SM Incidents reported against Drivers.

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[157] Weekend Late Night hours are defined as Friday, Saturday, and Sunday from 12:00 a.m. to 4:59 a.m. (a five-hour window each day). This results in 15 total hours (5 hours × 3 days). A week contains 168 hours (24 hours × 7 days). Therefore, Weekend Late Night hours represent 15 ÷ 168 = 0.089, or 8.9% of all hours in a week.

Figure 22: Distribution of SA/SM Incidents Against Drivers By Day of the Week and Time of Day
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

Figure 23: Distribution of SA/SM Incidents in the Five Safety Report Subcategories Against Drivers By Day of the Week and Time of Day (Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

Figure 24: Distribution of Rape and Attempted Rape Incidents Against Drivers By Day of the Week and Time of Day (Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

G. Uber's city boundaries do not align with local, state, or federally drawn city limits.

96. The following images exemplify how Uber defined cities, according to documents produced in advance of the October 14, 2025 Deposition of Sunny Wong. The fact that these city boundaries do not align with local, state, or federally designated cities precludes any per capita analysis involving population, as those data sources (e.g., Census Data) would be the source of population information. The following excerpted figures are from an Uber-produced document for this litigation and are unedited from their original production.

Figure 25: Screenshot of "City ID = 1 (San Francisco)" (Source: Gaddis Deposition Exhibit 2086)

City ID = 1 (San Francisco)

Figure 26: Screenshot of "City ID = 26 (Phoenix)" (Source: Gaddis Deposition Exhibit 2086)

City ID = 26 (Phoenix)

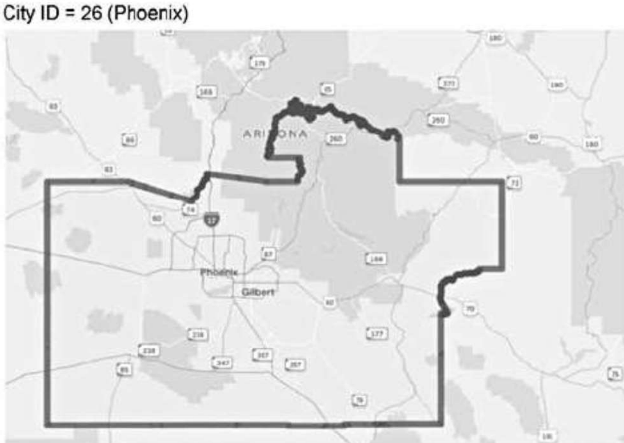
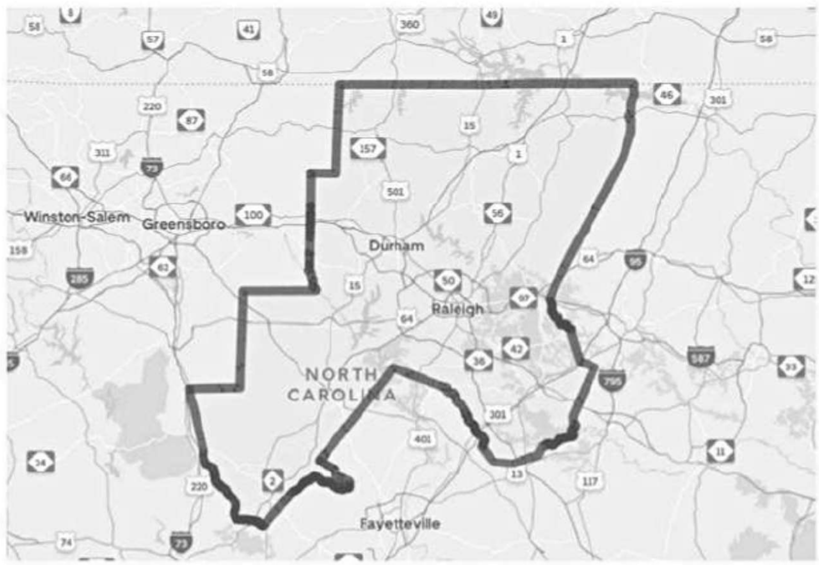


Figure 27: Screenshot of "City ID = 233 (Raleigh-Durham)" (Source: Gaddis Deposition Exhibit 2086)

City ID = 233 (Raleigh-Durham)



97. According to Uber's internally designated city boundaries, [redacted] had the highest volume of overall SA/SM Incident reports from 2017 to 2024, while [redacted] had the highest volume of SA/SM Incidents in the Five Safety Report Subcategories, as well as of Rape and Attempted Rape incidents specifically. The trips for Bellwether Plaintiff Dean and Bellwether Plaintiff [redacted] were categorized by Uber in its "Phoenix" city designation, which was [redacted] in the U.S. for SA/SM Incident reports [redacted], [redacted] for SA/SM Incidents in the Five Safety Report Subcategories, and [redacted] for Rape and Attempted Rape incidents. The trips for Bellwether Plaintiff Orozco and Bellwether Plaintiff Le were categorized by Uber in its "San Francisco" city designation, which was 9th in the U.S. for SA/SM Incident reports ([redacted]), 5th for SA/SM Incidents in the Five Safety Report Subcategories, and 7th for Rape and Attempted Rape incidents. Bellwether Plaintiff [redacted] trip was categorized by Uber in its "Raleigh-Durham" city designation, which was [redacted] in the U.S. for SA/SM Incident reports [redacted], [redacted] for SA/SM Incidents in the Five Safety Report Subcategories, and [redacted] for Rape and Attempted Rape incidents.

98. The following table shows the top twenty Uber-designated cities with the most SA/SM Incident reports. The table is limited to reports against Drivers. Because city boundaries do not align with local, state, or federally designated cities, any per capita analysis is precluded. Uber did not produce data that provided total trip volume by Uber-designated city, which also precludes me from providing an analysis of the incident rate by city. The table is sorted by number of trips with SA/SM reports, in descending order.

Table 11: Twenty Uber-Designated Cities with the Most Reported SA/SM Incidents Against Drivers
(Source: Flack SA/SM Incident Data, 2017-2024)

[redacted]

XI. Opinion 6: Uber Cultivated a Data-Rich Environment From Its Founding, and Implemented a Machine Learning Algorithm Nearly a Decade Later to "prevent sexual assaults."[158]

A. At Uber, "Data is Queen."[159]

99. Uber says that data is "crucial for [its] products"[160] and that technology is "at the heart" of its safety approach.[161] A 2021 Internal Audit at Uber reported that Uber was collecting five terabytes of data daily and relied on approximately 100,000 data tables to power its products.[162] As "a data-driven company, Uber makes every business decision based on large-scale data collected from the marketplace,"[163] with data-driven models contributing over [redacted], as of 2021.[164]

100. Uber's data capabilities are vast: since its launch in March 2009,[165] Uber has collected, maintained, and analyzed numerous data points from its trips, Drivers, and Riders, and leveraged these data points to develop new features, including new safety features.[166] The first SA/SM Incident was reported to Uber at least by December 2012.[167] Produced data and public reports indicate that Uber collected and maintained at least some information on trips with SA/SM Incidents at least as early as 2014.[168]

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[158] UBER_JCCP_MDL_003224079.
[159] UBER_JCCP_MDL_004991726; UBER-MDL3084-000000319.
[160] "How Data Shapes the Uber Rider App." Uber. https://www.uber.com/blog/how-data-shapes-the-uber-rider-app/.
[161] UBER-MDL3084-000000319.
[162] UBER_JCCP_MDL_004991726.
[163] How Uber Achieves Operational Excellence in the Data Quality Experience." Uber. https://www.uber.com/blog/operational-excellence-data-quality/
[164] UBER_JCCP_MDL_004991726.
[165] "The History of Uber." Uber. https://www.uber.com/newsroom/history/
[166] Examples: UBER_JCCP_MDL_002296928; UBER_JCCP_MDL_001594498; UBER-MDL3084-000008501; UBER_JCCP_MDL_000254982; Uber_DOE_0008013; UBER_JCCP_MDL_000120998; UBER-MDL3084-000008501; UBER_JCCP_MDL_002296928; UBER_JCCP_MDL_001594498; UBER-MDL3084-000008501; UBER_JCCP_MDL_000254982; Uber_DOE_008013.
[167] July 3, 2025 Deposition of Travis Kalanick, p. 145-152 and Exhibit 1342.
[168] UBER_JCCP_MDL_002246503; Warzel & Bhulyan, "Internal Data Offers Glimpse At Uber Sex Assault Complaints," Buzzfeed, https://www.buzzfeednews.com/article/charliewarzel/internal-data-offers-glimpse-at-uber-sex-assault-complaints (Mar. 6, 2016) (Hourdajian Ex. 104).

B. Uber developed S-RAD in 2017 and launched S-RAD in 2022.

101. Uber learned, in part through mining its own data, that reported SA/SM Incidents were correlated with certain risk factors.[169] From 2016 to 2017, Uber developed and piloted a product called Safety Risk Assessed Dispatch ("S-RAD") to "prevent sexual assaults."[170] According to Uber: "[t]he S-RAD model leverages a variety of trip, driver, and rider-level predictors to detect driver-rider matches with elevated risk of sexual assaults."[171]

102. S-RAD has the following components and definitions:

102.1. "**Features**" or "**Predictors**":[172] Specific data inputs (e.g., [redacted]) that Uber has factored into the S-RAD model to identify risk of SA/SM Incidents for potential Driver-Rider pairings (which are also called "supply plans" by Uber).

102.2. **Machine Learning Model**:[173] At the point of potential Driver-Rider pairing, Uber uses a machine learning model, which leverages Features to generate an S-RAD score for each potential Driver-Rider pairing.

102.3. **S-RAD score**:[174] A computed numerical score between [redacted] for each potential Driver-Rider pairing."

102.4. **S-RAD threshold**:[175] Uber flags and potentially seeks to avoid potential Driver-Rider pairings with S-RAD scores [redacted]

[169] UBER_JCCP_MDL_003306684, p. 2, 26-30; UBER_JCCP_MDL_000031720, p. 3, 8-10.
[170] UBER JCCP MDL 001144266; UBER JCCP MDL 001101922; UBER_JCCP_MDL_003306684; UBER_JCCP_MDL_001730324; UBER_JCCP_MDL_003224079.
[171] UBER_JCCP_MDL_003306684 at 3306697.
[172] UBER_JCCP_MDL_003306684; UBER_JCCP_MDL_005784097.
[173] UBER_JCCP_MDL_003306684.
[174] UBER_JCCP_MDL_004929682, Column AK.
[175] UBER_JCCP_MDL_003602459.

102.5. **"Trigger-rate"**:[176] The percentage of higher-risk trips Uber flags and takes action upon. [redacted]

102.6. **"Soft Filtering" intervention**:[177] After Uber flags a potential Driver-Rider pairing with S-RAD, one intervention Uber has used is what Uber calls "soft filtering." Uber adds a penalty to the wait time score for potential Driver-Rider pairings that have a risk of SA/SM above the S-RAD threshold.[178] In other words, making it less likely that Uber will dispatch them.

102.7. **"Hard Filtering" intervention**:[179] In September 2023, Uber began using what Uber calls "hard filtering." While Uber calls this "hard filtering," this is a non-standard use of the term: potential Driver-Rider pairings are not always filtered out or blocked. With "hard filtering," Uber flagged potential Driver-Rider pairings above the S-RAD threshold unless all potential Driver-Rider pairings had S-RAD scores above the S-RAD threshold. In those cases, [redacted][136]

102.8. [redacted][180] Driver-Rider pairings that Uber flags as having a risk of SA/SM above its S-RAD threshold, but which it nonetheless dispatches.

102.9. **Holdout Group**:[181] Uber holds back [redacted] as a control group to study the effectiveness of SA/SM on an ongoing basis. For these potential Driver-Rider pairings, [redacted],"[182] meaning that Uber takes no action on them.[183]

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[176] UBER_JCCP_MDL_003602459.
[177] June 25, 2025 30b6 Deposition of Sunny Wong at 239:23-240:21; UBER_JCCP_MDL_002059019.
[178] UBER_JCCP_MDL_003224079.
[179] June 25, 2025 30b6 Deposition of Sunny Wong at 240:10-21.
[180] UBER_JCCP_MDL_002059019.
[181] UBER_JCCP_MDL_003602459.
[182] UBER_JCCP_MDL_003602459.
[183] June 25, 2025 Deposition of Sunny Wong at 233:10-234:1.

103. In 2017, Uber trained the S-RAD model on trips from 2016.[184] Between 2017 and 2018, Uber tested over 50 different versions of the model and considered over 200 inputs.[185] In the first version of the model, Uber ultimately incorporated 32 Features that were based on "correlates and precursors" of sexual assault.[186] The inputs that Uber found to be the most predictive of Driver-Rider pairings with an elevated risk of SA/SM included but were not limited to: the time of day, day of week, proximity of the pickup location to bars/restaurants, ratings of the Driver and Rider, and previous SA/SM Incidents against the Driver and Rider reported to Uber.[187]

104. When assessing S-RAD's performance after testing in 2018, Uber data scientist Sunny Jeon reported that "S-RAD may represent Uber's most effective intervention for preventing sexual assault."[188] Between 2018 and 2020, [redacted] that ran in multi-week intervals, ranging from two weeks to nearly six months.[189] During this time, [redacted] [190] [redacted]."[191] In 2020 and 2021, [redacted]

105. In July 2022, Uber deployed its "US Full Rollout" of S-RAD on a subset of all non-shared trips.[194] The S-RAD model in 2022 contained [redacted] [195] [redacted] that Uber incorporated into S-RAD five years prior in 2017.[196]

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[184] UBER_JCCP_MDL_003306684, p. 9.
[185] UBER_JCCP_MDL_003306684, p. 5.
[186] UBER_JCCP__MDL_003306684, p. 2.
[187] UBER_JCCP_MDL_003306684.
[188] July 23, 2025 case-specific Deposition of Sunny Wong at 100:10-16.
[189] UBER_JCCP_MDL_003224079 at p. 26; UBER_JCCP_MDL_001730324 at p. 37.
[190] UBER_JCCP_MDL_003224079 at p. 26.
[191] UBER_JCCP_MDL_003224079 at p. 26.
[192] UBER_JCCP_MDL_001730324 at p. 37.
[193] UBER_JCCP_MDL_000575334 at p.169.
[194] UBER_JCCP_MDL_003602082.
[195] UBER_JCCP_MDL_005784097 p. 2-3.
[196] UBER_JCCP_MDL_000031720.0025.

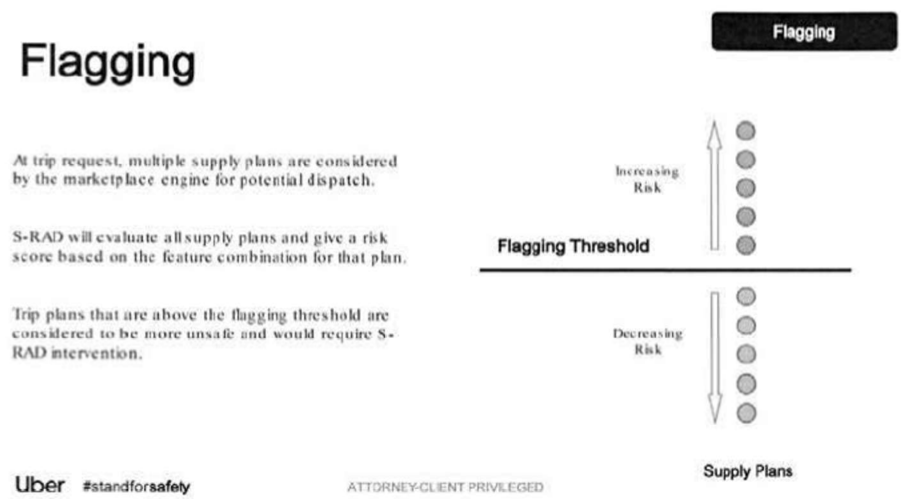
C. S-RAD dispatches some trips above the "Flagging Threshold."[197]

106. When a trip is requested, Uber scores each potential Driver-Rider pairing based on the risk of SA/SM Incidents with the goal of reducing the probability of SA/SM Incidents.[198] When Uber dispatches a Driver to a Rider, S-RAD is the only way Uber takes into account and attempts to reduce the risk of SA/SM Incidents.[199] Uber scores potential pairings [redacted][200]

107. The following figure is an illustration from Uber's internal documents that outlines how S-RAD flags certain trips.[201]

[197] UBER_JCCP_MDL_003224079.
[198] UBER_JCCP_MDL_002340857.
[199] June 25, 2025 Deposition of Sunny Wong at 232:18-233:9.
[200] UBER_JCCP_MDL_003224079.
[201] Other Uber programs are designed to block trips when flagged: Uber also developed the "Safe Dispatch Model (SDM)", which identifies and blocks requests that pose a potential risk to Driver or Rider safety on cash trips (UBER-MDL3084-000008501; UBER_JCCP_MDL_000960333, p.14).

Figure 28: "Trip plans that are above the flagging threshold are considered to be more unsafe and would require S-RAD intervention."
(Source: UBER_JCCP_MDL_003224079, page 8)



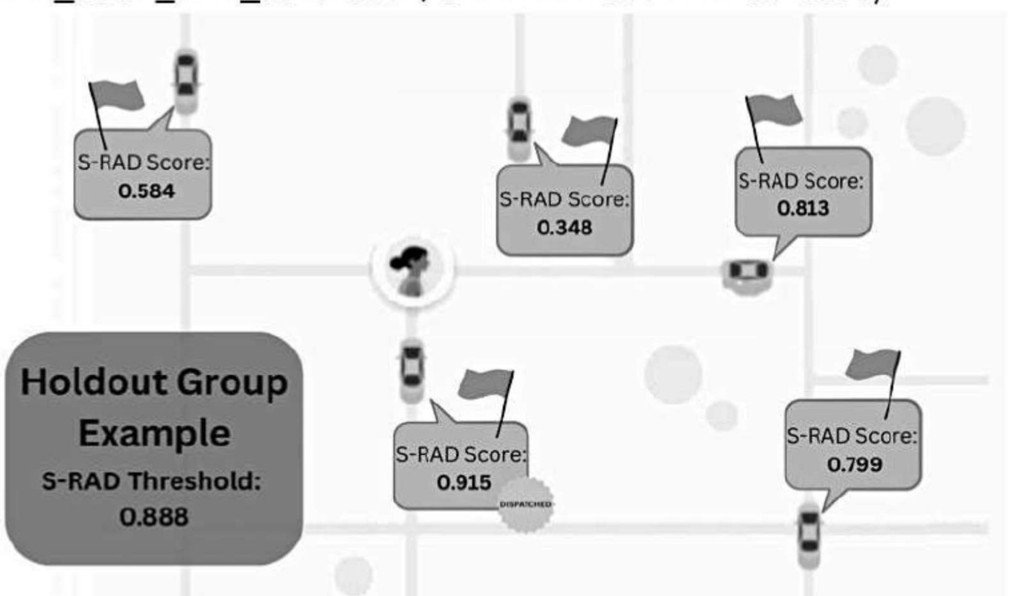
108. [redacted] as of the date of this report.[202] In late 2022, [redacted][203] [redacted]."[204]

[202] UBER_JCCP_MDL_003602459.
[203] UBER_JCCP_MDL_002059019.
[204] UBER_JCCP_MDL_002059019.

109. There are three ways in which potential Driver-Rider pairings are not actioned[205] by S-RAD:

109.1. **Holdout Groups**: Uber assigns [redacted]."[206] Trips in holdout groups do not receive intervention from the S-RAD program as long as they remain in the holdout group. In other words, Uber pairs Drivers and Riders but does not intervene based on the S-RAD score of a potential Driver-Rider pairing.[207] As an example shown in the following image, a potential Driver-Rider pairing in a temporary holdout group may receive an S-RAD score above the flagging threshold (here, hypothetically 0.888), but the Driver-Rider pairing will still be dispatched anyway.

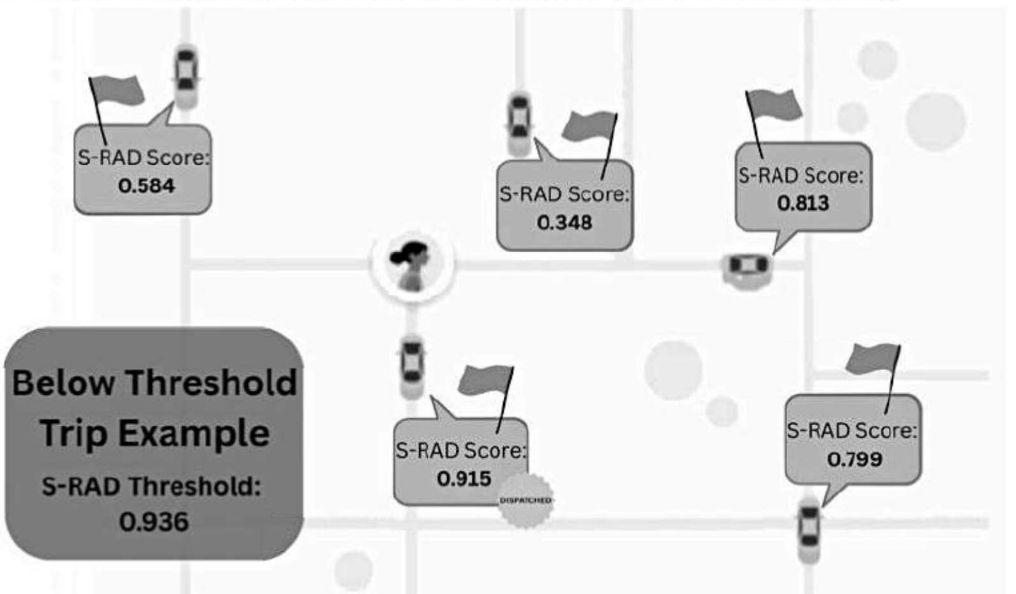
Figure 29: Example of a Driver-Rider Pairing in a Holdout Group[208]
(Source: UBER_JCCP_MDL_00908749.0044; UBER_JCCP_MDL_004929682; UBER-MDL3084-BW-0048903)



[205] Deposition of Sunny Wong at 157:18-158:25; 232:3-9; 273:10-14.
[206] UBER_JCCP_MDL_003602459.
[207] UBER_JCCP_MDL_003602459.
[208] This image is a hypothetical graphic based on data from UBER_JCCP_MDL_00908749.0044, UBER_JCCP_MDL_004929682, and UBER-MDL3084-BW-0048903.

109.2. **Below the S-RAD Threshold**: For potential Driver-Rider pairings below the flagging threshold, Uber does not use S-RAD to prioritize Driver-Rider pairings with lower S-RAD scores.[209] As an example shown in the following figure, among Driver-Rider pairings with S-RAD scores below the flagging threshold (here, hypothetically 0.936), Uber may dispatch the trip with the highest S-RAD score.

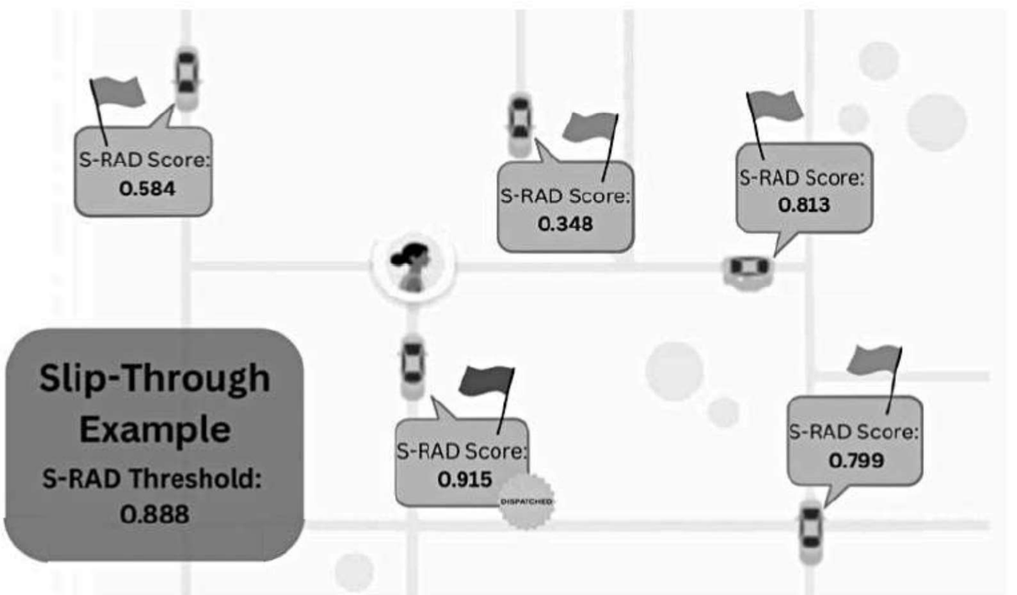
Figure 30: Example of Trip Where All Potential Pairings Are Below the S-RAD Threshold[210]
(Source: UBER_JCCP_MDL_00908749.0044; UBER_JCCP_MDL_004929682; UBER-MDL3084-BW-0048903)



[209] UBER_JCCP_MDL_003224079.
[210] This image is a hypothetical graphic based on data from UBER_JCCP_MDL_00908749.0044, UBER_JCCP DL_004929682, UBER-MDL3084-BW-0048903.

109.3. [redacted][212] As an example shown in the following image, a Driver with the lowest ETA but the highest S-RAD score could be dispatched.[213]

Figure 31: Example of a Trip With a Slip-Through[214] (Source: UBER_JCCP_MDL_00908749.0044; UBER_JCCP_MDL_004929682; UBER-MDL3084-BW-0048903)



[211] Uber has stated that [redacted]" (Bates No. UBER_JCCP_MDL_002340620; UBER_JCCP_MDL_002059019); UBER_JCCP_MDL_003274193.
[212] UBER_JCCP_MDL_003274193.
[213] UBER_JCCP_MDL_003224079; UBER_JCCP_MDL_003503729.
[214] This image is a hypothetical graphic based on data from UBER_JCCP_MDL_00908749.0044, UBER_JCCP_MDL_004929682, UBER-MDL3084-BW-0048903.

110. [redacted][215] [redacted][216] [redacted][217] [redacted][218] [redacted]."[219]

111. Between 2022 and 2023, Uber started piloting "nudges" as a way to "handle" the [redacted], or prompts for the Driver and Rider to consider turning on specific safety features such as Audio Recording, Follow My Ride, and Ride Check.[220] Uber testimony in this litigation indicates that [redacted][221] I have requested any nudge-related datasets or [redacted] datasets as they pertain to the Bliss/Jira SA/SM Incident Data or Flack SA/SM Incident Data in the United States, but understand that they have not been provided as of the date of this report.

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[215] UBER_JCCP_MDL_003274193 p. 53. "50/50 Safety XP" Column; For context, in the United States during those months, there were 3,319 Serious Sexual Assault and Sexual Misconduct incidents reported, according to the Updated Flack Incident Report Classification Data from September 2021 through April 2022. Because Uber has not produced comprehensive information on S-RAD scores and thresholds, it is not possible for me to do any independent analysis of these figures.

[216] UBER_JCCP_MDL_003274193 p. 53. "50/50 Safety XP" Column; For context, in the United States during those months, there were 3,966 Serious Sexual Assault and Sexual Misconduct incidents reported, according to the Updated Flack Incident Report Classification Data from July 2022 through December 2022.

[217] UBER_JCCP_MDL_003274193.

[218] UBER_JCCP_MDL_003274193; Deposition of Sunny Wong, 6/25/2025, p. 128; p. 129.

[219] September 24, 2025 Declaration of Sunny Wong. This number was stated without any reference to geography or time frame.

[220] UBER JCCP MDL 002658347; UBER_JCCP_MDL_000149159; UBER_JCCP_MDL_001461771.

[221] UBER JCCP MDL 002658347. *See* Doc. No. 4009-8 (September 23, 2025, Declaration of Sunny Wong, 34) ("[redacted]).

D. [redacted]

112. [redacted] At various times between 2017 and 2022 [redacted] Documents from September 2017 show that [redacted]

[222] UBER_JCCP_MDL_003224079.
[223] UBER_JCCP_MDL_003385297.
[224] UBER_JCCP_MDL_003385297.
[225] UBER_JCCP MDL_003306684.
[226] UBER_JCCP_MDL_003385297.
[227] UBER_JCCP_MDL_005025910.

Figure 32: Uber Document Estimates That [redacted] from November 1, 2022 through January 31, 2023 (Source: UBER_JCCP_MDL_005025910 p.11)

[redacted]

113. Ultimately, Uber selected a [redacted] for all U.S. trips [redacted][228] [redacted][229] In other words, although 100% of potential Driver-Rider pairings are scored by S-RAD, for [redacted], Uber does not intervene with S-RAD.

[228] In a 2021 correspondence, Uber's Chief Technology Officer asked: [redacted] (Bates No. UBER_JCCP_MDL_003220912). An email response to this question stated: [redacted] (Bates No. UBER_JCCP_MDL_003384231, 4/13/2021; UBER_JCCP_MDL_005620999, 4/13/2021). [redacted] (Bates No. UBER_JCCP_MDL_003224079). [redacted] (Bates No. UBER_JCCP_MDL_003224079).

[229] UBER_JCCP_MDL_005025910; Deposition of Sunny Wong, June 25, 2025, p. 255.

E. Bellwether Plaintiffs' S-RAD Scores

114. Uber produced some information about S-RAD scores for the Bellwether Plaintiffs.[230] In the following section, I include overall trip S-RAD scores for the trip associated with Uber Drivers dispatched to each Bellwether Plaintiff as well as the inputs associated with S-RAD features that Uber analyzed as "precursors"[231] to SA/SM Incidents, including bars and restaurants near to the pick-up location, Driver's previous Safety Incident reports (e.g., interpersonal crime incidents ("IPC"), SA/SM Incidents), Driver 1- and 2- star ratings,[232] and Driver weekend and late-night request rates.[233]

115. Because Uber has not produced comprehensive information on how any S-RAD scores and thresholds were calculated or weighted, nor the relative scores of other available Driver-Rider pairings, it is not possible for me to translate any particular score in terms of what it means for the risk of an SA/SM Incident.

116. The following are the S-RAD scores that Uber produced as composite scores for the Bellwether Plaintiffs.[234] Further details on specific S-RAD features that were included in the S-RAD models that were applied to Plaintiff-Driver pairs at the times of their incidents are available in Updated Keller Report Appendix F.

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[230] UBER-MDL3084-BW-00048903; UBER-MDL3084-BW-00048906; UBER-MDL3084-BW-00048904; UBER-MDL3084-BW-00048905.
[231] UBER_JCCP_MDL_000964270.
[232] In 2023, Uber removed Driver feedback (i.e., 1-star ratings) from the S-RAD model. It was the second most important bundle in the first version of the model (Bates No. UBER_JCCP_MDL_005025910, p. 3, p. 18; UBER_JCCP_MDL_003274193, p. 86).
[233] UBER_JCCP_MDL_000031720; UBER_JCCP_MDL_001687315; UBER_JCCP_MDL_003306684; UBER_JCCP_MDL_000031720; UBER_JCCP_MDL_000031720.0009.
[234] Uber did not produce information as to how these scores were calculated.

Table 12: Bellwether Plaintiff S-RAD Scores and Select Feature Values
(Source: UBER-MDL3084-BW-00048903, UBER-MDL3084-BW-00048904, UBER-MDL3084-BW-00048905, UBER-MDL3084-BW-00048906)

[redacted]

XII. Conclusion[235]

117. Given my analyses, my review of documents and data, and my professional experience, it is my opinion that Uber disclosed in its U.S. Safety Reports no more than 3.2% of the 392,828 SA/SM Incidents that it received, classified into SA/SM Incident Subcategories, and retained in Flack from 2017 through 2022, and that Uber has not disclosed more than 97.7% of the SA/SM Incidents it tracked between 2017 through 2024.

118. It is my further opinion that Uber internally designated Subcategories of SA/SM Incidents as "Serious SA/SM" but did not publicly disclose them. Between 2017 and 2022, Uber received, classified into SA/SM Incident Subcategories, and retained in Flack reports of [redacted] SA/SM Incidents as "Serious SA/SM" and did not disclose [redacted] of those incidents in its U.S. Safety Reports. As of the date of this report, Uber has not disclosed [redacted] of the SA/SM Incident reports it classified in Flack from 2017 through 2024 as "Serious SA/SM".

119. It is also my opinion that from 2017 through 2024, Uber received an SA/SM Incident report the equivalent of every eight minutes, and a report of Rape or Attempted Rape the equivalent of [redacted]. I further conclude that, after Covid in 2020, both the number and rate of SA/SM Incidents increased every year from 2021 through the end of the data period. Specifically for Rape, [redacted].

120. It is also my opinion that Uber tracked which of its Drivers had prior SA/SM Incidents and internally discussed prior to the publication of its first U.S. Safety Report that having a prior SA/SM Incident made a Driver more likely to be reported for SA/SM again. I further conclude that approximately [redacted] SA/SM Incidents reported against Uber Drivers involved Drivers who had already been reported once to Uber for SA/SM.

121. It is my further opinion that Uber's Flack system includes [redacted] I conclude that Uber audited a vast majority of the 546,420

[235] This section is not intended to provide a comprehensive summary of my opinions.

trips retained in Flack that had SA/SM Incidents. I also conclude that the data Uber retained in Flack showed the majority of Rape and Attempted Rape incidents were reported against Drivers, and that a disproportionate volume of SA/SM Incidents occurred during Weekend Late Nights.

122. It is my further opinion that Uber internally discussed "precursors" to SA/SM Incidents, but it did not disclose that information in the U.S. Safety Reports.

123. It is my further opinion that Uber cultivated a data-rich environment from its founding, had extensive data capabilities,[236] and did not develop S-RAD until 2017. I also conclude that Uber did not deploy S-RAD until 2022 to address SA/SM Incidents on its platform.

124. Finally, it is my opinion that Uber collected data and information regarding the Plaintiff Bellwethers' trips, including data on the Drivers of those trips. I also conclude that this data resembled the information of other documents and data produced for other SA/SM Incidents, and that all but two of the Bellwether trips [redacted]) were contained in the Flack SA/SM Incident Data.

LACEY R. KELLER

[236] Examples: UBER_JCCP_MDL_002296928; UBER_JCCP_MDL_001594498; UBER-MDL3084-000008501; UBER_JCCP_MDL_000254982; Uber_DOE_0008013; UBER_JCCP_MDL_000120998; UBER-MDL3084-000008501; UBER_JCCP_MDL_002296928; UBER_JCCP_MDL_001594498; UBER-MDL3084-000008501; UBER_JCCP_MDL_000254982; Uber_DOE_0008013.

IN THE UNITED STATES COURT

FOR THE NORTHERN DISTRICT OF CALIFORNIA

In re. Uber Technologies, INC., Passenger Sexual Assault Litigation	Case No. 3:23-md-03084-CRB

Updated Expert Report of Lacey R. Keller ("Updated Keller Report") Appendix A - Methodology

Dated: December 2, 2025

Confidential and Subject to Protective Order

I. Core Tenets of Data Mining and Analytics

1. As stated in my report and further discussed in Keller Report - Appendix C, I am an expert in Data Mining and Analytics. Data Mining and Analytics uses systematic data preparation and exploration to find patterns, trends, and relationships in order to develop useful, understandable, and sometimes actionable insights for others relying upon both structured and unstructured data.[1] Data Science is an interdisciplinary field that combines concepts and lessons from statistics, mathematics, computer science, management science, and engineering.[2] In my experience, Data Mining and Analytics often overlaps with Data Science, which uses the core tenets of Data Mining and Analytics but also builds predictive models using artificial intelligence and machine learning. A data analyst will provide more descriptive analytics using Excel, SQL, and other data visualization tools, while a data scientist will often provide predictive and prescriptive analytics, using programming languages such as Python[3] or R, and engage in data mining.[4] As an expert in Data Mining and Analytics, my work employs the common toolset of a Data Scientist (e.g., Python, SQL) to service descriptive analytics of that of an analyst; hence, Data Mining & Analytics.

2. The foundations of Data Mining and Analytics and Data Science lie in statistics, where methods such as regression and hypothesis testing were formalized in the 19th and early 20th centuries by figures like Gauss, Fisher, and Neyman–Pearson.[5] Starting in the mid-1950s, businesses started using computerization, with only one computing resource in the organization, known as "the mainframe."[6] In 1960, John Tukey published a paper entitled "The Future of Data Analytics," which framed data analytics as its own discipline.[7] In 1970, Edgar Codd published a paper describing the first relational database, where data is stored in simple tables with rows and fields that can be queried by users -

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[1] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.

[2] VanderPlas, J. (2016). *Python data science handbook*. O'Reilly Media. https://www.oreilly.com/library/view/python-data-science/9781491912126/; Siadati, S. (2021). *Data science foundations* (Version 1.1) [E-book]. Zenodo. https://doi.org/10.5281/zenodo.17010182; https://www.tandfonline.com/doi/epdf/10.1080/10618600.2017.1384734?needAccess=truehttps://dl.acm.org/doi/pdf/10.1145/3076253

[3] Walsh, Introduction to Cultural Analytics & Python, Version 1, 2021;Deitel& Deitel, 2000, Intro to Data Science; Deitel.& Deitel. 2019. Intro to Python for Data Science, Pearson; VanderPlas, 2017, Python Data Science Handbook, 1st Ed, O'Reilly; VanderPlas, 2017, Python Data Science Handbook, 1st Ed, O'Reilly

[4] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.

[5] Lehmann, E. L. (2011). *Fisher, Neyman, and the Creation of Classical Statistics*. Springer. 2025, https://link.springer.com/book/10.1007/978-1-4419-9500-1

[6] Rainer, R. K., Jr., & Prince, B. (2023). Introduction to information systems: Supporting and transforming business (10th ed.). Wiley.

[7] Tukey, J. W. (1962). The future of data analysis. *Annals of Mathematical Statistics, 33*(1), 1–67.

a method employed still today, including for this report.[8] Starting in the late 1970s, the first personal computers appeared, and in 1981, the IBM PC debuted as the first in the market, after which users began utilizing their own personal computers, including spreadsheet and word processing applications.[9] The programming language, Python, was developed in 1991 by Guido van Rossum.[10] The formal use of the term Data Mining began that same decade,[11] and through the 2000s, advances in cloud computing, open-source programming languages, and machine learning libraries expanded these capabilities, giving rise to a field that is now widely called Data Science.[12]

3. In just 20 years, from 2000 to 2020, the proportion of digital storage in the world surged from 25% to 98%, while the remaining consisted of other storage.[13] Today, data analysts and data scientists are essential to nearly every sector of the economy, allowing organizations to process massive volumes of information, identify trends, and make evidence-based decisions. The rapid growth of the data analysis and data science fields fueled the technology boom of the 1990s and continues to shape the current era, as artificial intelligence becomes widely accessible across industries.[14] Data science has become essential for data-heavy modern businesses, particularly those in the "tech" industry, like Uber.[15]

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[8] Codd, E. F. (1970). A relational model of data for large shared data banks. *Communications of the ACM, 13*(**6**), 377–387; Keller, L., & Nelson, E. (2022, September). Structured data. *Bloomberg Law: Practical Guidance, Litigation, Professional Perspective*. Bloomberg Law. https://www.bloomberglaw.com/external/document/X1PD0P3S000000/litigation-professional-perspective-structured-data.

[9] Rainer, R. K., Jr., & Prince, B. (2023). Introduction to information systems: Supporting and transforming business (10th ed.). Wiley.

[10] "Python is a widely-used, interpreted, object-oriented, and high-level programming language with dynamic semantics, used for general-purpose programming." https://pythoninstitute.org/about-python

[11] https://www.sas.com/en_us/insights/analytics/data-mining.html

[12] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.

[13] Rainer, R. K., Jr., & Prince, B. (2023). Introduction to information systems: Supporting and transforming business (10th ed.). Wiley.

[14] Basu, S., Fernald, J. G., & Shapiro, M. D. (2001). Productivity growth in the 1990s: technology, utilization or adjustment? *Carnegie-Rochester Conference Series on Public Policy*, *55*(1). https://doi.org/https://www.sciencedirect.com/science/article/abs/pii/S0167223101000549

[15] *See e.g.*:
Donoho, D. (2017). 50 Years of Data Science. *Journal of Computational and Graphical Statistics*, *26*(4), 745–766. https://doi.org/https://www.tandfonline.com/doi/epdf/10.1080/10618600.2017.1384734?needAccess=true; Cao, L. (2017). Data Science: A Comprehensive Overview. *ACM Computing Surveys*, *50*(3). https://doi.org/https://dl.acm.org/doi/pdf/10.1145/3076253; Siadati, S. (2021). *Data Science Foundations* (1.1). September 2025, https://www.researchgate.net/profile/Saman-Siadati/publication/395109847_Data_Science_Foundations/links/68b3afc2360112563e0f7e60/Data-Science-Foundations.pdf

4. Data can be structured, unstructured, or semi-structured.[16] I have spoken at numerous conferences and published articles on the use of structured and unstructured data, specifically for use in investigations and litigation. Structured data is that that is machine-readable data, meaning that it is easily processed by a computer. The average person may encounter structured data through formats such as a CSV or Excel spreadsheet; however, structured data takes on other forms (e.g., JSON, XML, HTML) for those working in the field of Data Mining and Analytics and/or Data Science. Unstructured data is typically text-based data, but also might include photos and videos. Text-based unstructured data can be turned into structured data by using keyword searches and natural language processing to extract key phrases or dates, as an example.

5. Specifically, in this report, I have used four fundamental tenets of Data Mining and Analytics:

Step 1: Data Preparation (ETL)[17]

6. Before meaningful analysis can occur, raw data must undergo preparation, often known as the extraction, transformation, and loading process ("ETL") – also known sometimes less formally as "wrangling." This process involves collecting and consolidating data from multiple sources and then cleaning/standardizing and transforming it into a consistent format amenable to analysis. Cleaning/standardization typically requires identifying and addressing erroneous and inconsistent values (e.g., Kansas, KS, ks, Kansas), placeholders for null values (e.g., \N, NULL''), or irregular data types (e.g., dates stored as text fields). Under certain circumstances, data preparation involves creating additional fields (known as data enrichment) to assist with the data analysis and reconciling duplicate entries.[18]

Step 2: Data Validation[19]

7. Validation is the process of ensuring that data is accurate and reliable before being used. In practice, this involves checking data quality, confirming that

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[16] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.; https://www.tandfonline.com/doi/full/10.1080/10618600.2017.1384734#d1e1118

[17] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.; https://www.tandfonline.com/doi/full/10.1080/10618600.2017.1384734#d1e1118

[18] Siadati, S. (2021). *Data Science Foundations* (1.1). September 2025, https://www.researchgate.net/profile/Saman-Siadati/publication/395109847_Data_Science_Foundations/links/68b3afc2360112563e0f7e60/Data-Science-Foundations.pdf

[19] Donoho, D. (2017). 50 Years of Data Science. Journal of Computational and Graphical Statistics, 26(4), 745–766. https://doi.org/10.1080/10618600.2017.1384734

preprocessing steps were applied correctly, and cross-checking outputs against known benchmarks or domain knowledge to identify possible issues.[20]

Step 3: Descriptive Analytics & Visualization[21]

8. Descriptive analytics focuses on summarizing historical data to answer the question, "what happened?" It uses measures such as averages, distributions, and percentages to provide an overview of past events, including outlier detection, trend analysis, and pattern recognition.[22] While descriptive analytics does not predict future outcomes, it forms the foundation for more advanced approaches such as predictive and prescriptive modeling.

9. As part of the descriptive analytics process, visualization transforms raw numbers into graphical representations (i.e., charts, plots, dashboards, maps) to make the data easier to interpret and communicate.[23] The four pillars of data visualization include: 1) clear purpose, 2) relevant content, 3) appropriate structure, 4) useful formatting.[24] Several libraries in Python exist exclusively for creating visualizations, for example Matplotlib,[25] Plotly,[26] and Seaborn.[27] These allow the user creating images to nearly infinitely customize their visualisations, by changing the font, color scheme, axis labels, and titles of the visualizations they create. Entire websites and blogs exist solely for data scientists to share the beautiful and effective images that they create.[28]

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[20] Siadati, S. (2021). *Data Science Foundations* (1.1). September 2025, https://www.researchgate.net/profile/Saman-Siadati/publication/395109847_Data_Science_Foundations/links/68b3afc2360112563e0f7e60/Data-Science-Foundations.pdf

[21] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.; https://www.consoleflare.com/blog/wp-content/uploads/2022/09/Exploratory-Data-Analysis-1977-John-Tukey.pdf; Tukey, 1962 https://projecteuclid.org/journals/annals-of-mathematical-statistics/volume-33/issue-1/The-Future-of-Data-Analysis/10.1214/aoms/1177704711.full; Siadati, S. (2021). *Data Science Foundations* (1.1). Self. September 2025, https://www.researchgate.net/profile/Saman-Siadati/publication/395109847_Data_Science_Foundations/links/68b3afc2360112563e0f7e60/Data-Science-Foundations.pdf; Donoho, D. (2017). 50 Years of Data Science. Journal of Computational and Graphical Statistics, 26(4), 745–766. https://doi.org/10.1080/10618600.2017.1384734

[22] Sharda, R., Delen, D., & Turban, E. (2017). Business intelligence, analytics, and data science: A managerial perspective (4th ed.). Pearson.

[23] Rainer, R. K., Jr., & Prince, B. (2023). Introduction to information systems: Supporting and transforming business (10th ed.). Wiley.

[24] Illinsky, IBM Center, 2021; https://guides.lib.berkeley.edu/data-visualization/about

[25] Hamowo, A. (2023) *Data visualization (DA 348 - Data discovery and management) [PDF slides].* Washburn University, School of Business.

[26] McKinney, W. (2010). Data Structures for Statistical Computing in Python. In S. van der Walt & J. Millman (Eds.), Proceedings of the 9th Python in Science Conference (pp. 56-61).

[27] Waskom, M. L., (2021). seaborn: statistical data visualization. Journal of Open Source Software, 6(60), 3021, https://doi.org/10.21105/joss.03021

[28] For example, https://informationisbeautiful.net/, https://visualisingdata.com/, https://flowingdata.com/.

Step 4: Automation

10. To ensure reproducibility and operational continuity, work should be scripted and documented in a transparent manner. Scripts should be written with clear comments and organization, supported by a README file that outlines essential information about a project, including (but not limited to) the order in which scripts should be executed and any other intricacies that users running the should know.[29]

II. Tools and Software Employed

11. I was required by an agreement between the Defendants and Plaintiffs[30] to work within a secure environment. To effectuate the production of data responsive to the Courts' Orders, Uber retained BDO USA as a Third-Party Administrator and Auditor for an Amazon Web Services (AWS) platform to manage the production, access, and use of Bliss/Jira SA/SM Incident Data and Flack SA/SM Incident Data and the resources necessary to analyze it ("AWS Secure Environment").

12. Per my specifications, the AWS Secure Environment was provisioned with the following services: 1) EC2 (virtual computing), 2) AWS Redshift SQL database (database and virtual computing), 3) SageMaker (machine learning and virtual computing) 4) GitTechnology through GitLabs (tracked changes for code) 5) VSCode (writing and executing code) to facilitate my analysis. I primarily relied upon the AWS Redshift SQL database and Python (via Jupyter notebooks in VS Code, which was installed in the AWS Secure Environment) for my work. Within Python, I utilized the following industry-standard libraries: Pandas,[31] NumPy,[32]

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[29] Liu, J., Calrson, J., Pasek, J., Puchala, B., Rao, A., & Jagadish, H. V. (2022). Promoting and enabling reproducible data science through a reproducibility challenge. *Harvard Data Science Review, 4(3).* https://doi.org/10.1162/99608f92.9624ea51

[30] *In Re: Uber Technologies, Inc. Passenger Sexual Assault Litigation,* United States District Court, Northern District of California Case, No. 3:23-md-03084-CRB, Appendix A to Confidentiality Agreement between BDO USA and Plaintiffs' Steering Committee.

[31] McKinney, W. (2010). Data Structures for Statistical Computing in Python. In S. van der Walt & J. Millman (Eds.), Proceedings of the 9th Python in Science Conference (pp. 56-61).; The Developer of pandas now works as Principal Architect @ Posit, Chief Scientist @ Voltron Data, GP @ Composed Ventures. (n.d.). Home [LinkedIn page]. LinkedIn. Retrieved September 25, 2025, from https://www.linkedin.com/in/wesmckinn/

[32] VanderPlas, 2017, Python Data Science Handbook, 1st Ed, O'Reilly

boto3,[33] botocore,[34] sqlalchemy,[35] pytz,[36] plotly,[37] and matplotlib.[38] The environment in which I worked is documented through a YAML file and has been disclosed with my other code. This file specifies all the packages employed, as well as their version numbers, to allow for reproducibility and to avoid installation or configuration issues that might arise in other environments.

13. I developed several custom tools and functions to assist me in loading the data and creating the report. Those scripts have also been disclosed with my other code.[39]

14. The AWS Secure Environment provided me with access to specific S3 Buckets (i.e., file storage) using the following structure:

14.1. **Bucket 1 Produced Data:** allows the Defendant Team to upload data and keep a record of all data that has been uploaded.[40]

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[33] Amazon Web Services, Inc. (n.d.). boto3: AWS SDK for Python. https://boto3.amazonaws.com/v1/documentation/api/latest/index.html

[34] Amazon Web Services, Inc. (n.d.). botocore: Low-level interface to AWS services. https://botocore.amazonaws.com/v1/documentation/api/latest/index.html

[35] SQLAlchemy Authors. (n.d.). SQLAlchemy: Database Toolkit and Object Relational Mapper. https://www.sqlalchemy.org/

[36] Lemburg, M. A., & Contributors. (2024). pytz: World Timezone Definitions for Python (Version 2024.1) [Computer software]. Python Package Index. https://pypi.org/project/pytz/

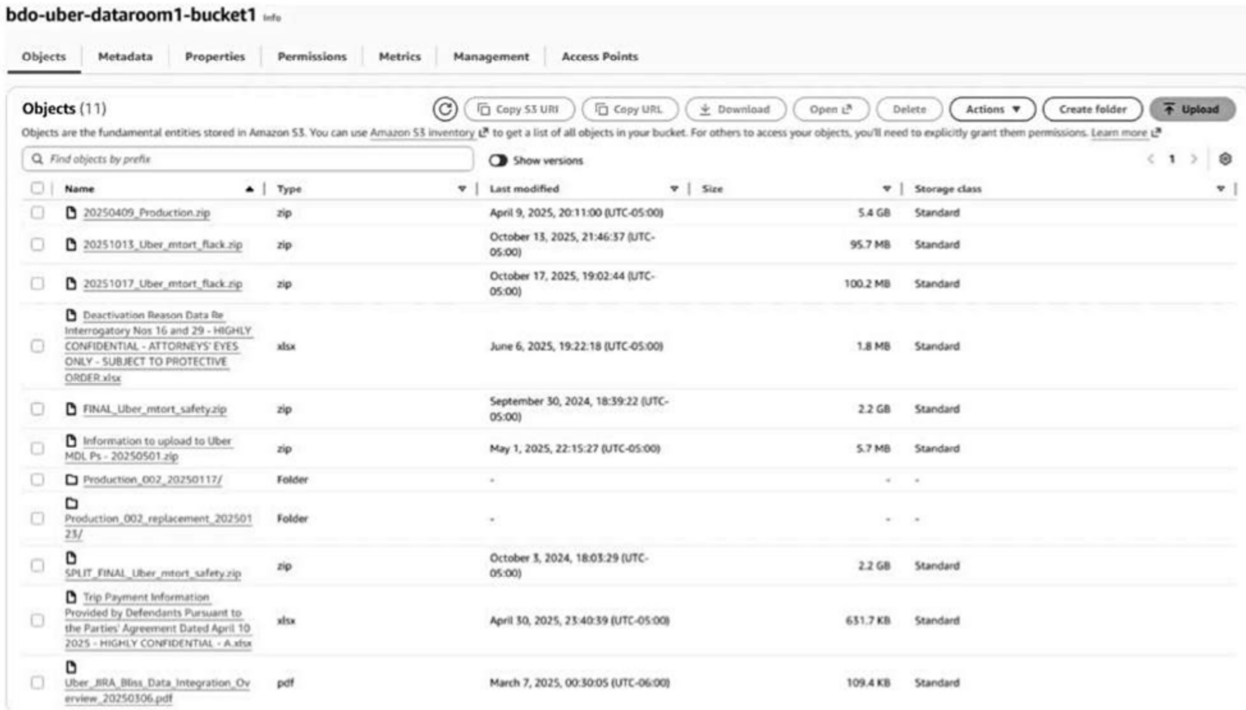
[37] Sievert C (2020). Interactive Web-Based Data Visualization with R, plotly, and shiny. Chapman and Hall/CRC. ISBN 9781138331457, https://plotly-r.com.

[38] J. Hunter, et al., matplotlib: Python plotting, http://matplotlib.sourceforge.net/

[39] report_helpers.py; aws_redshift_utils.py.

[40] Bucket 1m: Plaintiff Disclosures: this allows the Plaintiff Team to transfer code and output disclosures to the Defendant Team.

Figure 1: Screenshot of "Bucket 1"


bdo-uber-dataroom1-bucket1 Info

Objects | Metadata | Properties | Permissions | Metrics | Management | Access Points

Objects (11)

Copy S3 URI | Copy URL | Download | Open | Delete | Actions | Create folder | Upload

Objects are the fundamental entities stored in Amazon S3. You can use Amazon S3 inventory to get a list of all objects in your bucket. For others to access your objects, you'll need to explicitly grant them permissions. Learn more

Find objects by prefix | Show versions | 1

Name	Type	Last modified	Size	Storage class
20250409_Production.zip	zip	April 9, 2025, 20:11:00 (UTC-05:00)	5.4 GB	Standard
20251013_Uber_mtort_flack.zip	zip	October 13, 2025, 21:46:37 (UTC-05:00)	95.7 MB	Standard
20251017_Uber_mtort_flack.zip	zip	October 17, 2025, 19:02:44 (UTC-05:00)	100.2 MB	Standard
Deactivation Reason Data Re Interrogatory Nos 16 and 29 - HIGHLY CONFIDENTIAL - ATTORNEYS' EYES ONLY - SUBJECT TO PROTECTIVE ORDER.xlsx	xlsx	June 6, 2025, 19:22:18 (UTC-05:00)	1.8 MB	Standard
FINAL_Uber_mtort_safety.zip	zip	September 30, 2024, 18:39:22 (UTC-05:00)	2.2 GB	Standard
Information to upload to Uber MDL Ps - 20250501.zip	zip	May 1, 2025, 22:15:27 (UTC-05:00)	5.7 MB	Standard
Production_002_20250117/	Folder	-	-	-
Production_002_replacement_20250123/	Folder	-	-	-
SPLIT_FINAL_Uber_mtort_safety.zip	zip	October 3, 2024, 18:03:29 (UTC-05:00)	2.2 GB	Standard
Trip Payment Information Provided by Defendants Pursuant to the Parties' Agreement Dated April 10 2025 - HIGHLY CONFIDENTIAL - A.xlsx	xlsx	April 30, 2025, 23:40:39 (UTC-05:00)	631.7 KB	Standard
Uber_JIRA_Bliss_Data_Integration_Overview_20250306.pdf	pdf	March 7, 2025, 00:30:05 (UTC-06:00)	109.4 KB	Standard

14.2. Bucket 2: Plaintiff Only Workspace: this is the Plaintiff Team's workspace and only the Plaintiff Team can add, edit, delete, and remove files within the AWS Secure Environment. The Defendant Team does not have access. No work can be downloaded outside of the AWS Secure Environment from this folder. An "Ingress" bucket was added to allow the Plaintiff Team to upload data from outside the AWS Secure Environment to the AWS Secure Environment.

14.3. Bucket 3: Defendant Only Workspace: This is the equivalent of Bucket 2, but made for the Defendant Team. The Plaintiff Team does not have access.

14.4. Bucket 4: Plaintiff Downloads: this allows the Plaintiff Team to transfer work product to be downloaded outside of the AWS Secure Environment. The Defendant Team does not have access.

14.5. Bucket 5: Defendant Downloads: This is the equivalent of Bucket 4, but for the Defendant Team. The Plaintiff Team does not have access.

III. Methodology

15. For each of the five fundamental tenets of Data Mining and Analytics, I describe the steps I took for each dataset, with one section for each tenet and a subsection for each dataset.

Step 1: Data Preparation (ETL)

16. This section details the steps that I took to prepare each dataset, with one subsection for each dataset that was processed.

Interrogatories Nos. 1 through 8 ("Bliss/Jira Incident Report Classification Data," "Flack Incident Report Classification Data," "Updated Flack Incident Report Classification Data" and collectively, "Incident Report Classification")

17. Uber produced the Bliss/Jira Incident Report Classification Data and the Updated Flack Incident Report Classification Data outside of the AWS Secure Environment "Bucket 1." I copied the contents of those files onto the AWS Secure Environment by uploading them to the "Bucket 2" ingress using the web-based upload feature in the Amazon Console.

18. Once loaded, I cleaned the datasets to make the fields consistent for analysis, which included reformatting date fields so that month formatting aligned across datasets (e.g., "2025-09" to represent September 2025) and standardizing field names. I also standardized inconsistent formatting of spaces around dashes ("-") or slashes ("/") that were present in the "Category" column. Both datasets were formatted such that each row was a Category, with a column for each month of data. I removed any "total" rows from this data and processed them separately so as not to create inaccurate calculations later in my analysis. I then pivoted the data into a consistent format where each row represented a single month or year and Category. I added two fields: 1) translating the "Category" to the corresponding Subcategories as they are reported in Uber's published Safety Reports, and 2) identifying which Categories are considered to be "Serious SA/SM" by Uber.[41]

[41] UBER_JCCP_MDL_001730535 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 52-67 and Exhibit 3103; Apr. 16, 2025 Deposition of Sunny Wong, p. 187-193 and Exhibit 2810-b; Apr. 2, 2025 Deposition of Rebecca Payne, p. 93-98 and Exhibit 2508b); UBER_JCCP_MDL_000250826 (Apr. 24, 2025 Deposition of Katherine McDonald, p. 92-95 and Exhibit 3108). I note that Ms. McDonald gives inconsistent testimony about the categorization of Indecent photography/Videography Without Consent." I considered that Subcategory "non-serious" based on Ms. McDonald's testimony on p. 61 to 62 and 64 to 66, as well as Mr. Wong and Ms. Payne's corroborating testimony.

19. For the Bliss/Jira Incident Report Classification data specifically, I extracted the rows labeled "Total # of Completed Rides Trips" and "Total # of Unique Rides Trips with a Reported Incident,"[42] keeping the month and values from the data separately from the Category-level data.

Interrogatory No. 28

20. Uber produced Interrogatory No. 28 into AWS S3 "Bucket 1," which permitted only read access to the data. I downloaded the data from "Bucket 1" using command-line tools executed via Python onto the AWS Secure Environment and uploaded the data into "Bucket 2" for further processing and analysis. From there, I then loaded all files into the AWS Redshift SQL database using Python. No additional cleaning or standardization was necessary for this file.

Interrogatory No. 16/29 and Interrogatory No. 16/29 Addendum

21. Uber produced Interrogatory No. 16/29 and Interrogatory No. 16/29 Addendum into AWS S3 "Bucket 1," which permitted only read access to the data. I downloaded the data from "Bucket 1" using command-line tools executed via Python onto the AWS Secure Environment and uploaded the data into "Bucket 2." From there, I then loaded all files into the AWS Redshift SQL database using Python. No additional cleaning or standardization was necessary for this file.

Bliss/Jira SA/SM Incident Data

22. Pursuant to Appendix A to Confidentiality Agreement between BDO USA and Plaintiffs' Steering Committee, Uber produced the Bliss/Jira SA/SM Incident Data into AWS S3 "Bucket 1," which permitted only read access to the data. I downloaded the data from "Bucket 1" using command-line tools executed via Python onto the Amazon Workspace provisioned by BDO.

23. The files were produced as a compressed .zip file, which I extracted in the AWS Secure Environment. Again, using command-line tools executed via Python, I uploaded the data into "Bucket 2" for further processing and analysis. I deleted the .zip file and associated extracted files from the AWS Secure Environment.

24. I then loaded all files into the AWS Redshift SQL database using Python. While the Jira tables were small enough to load directly into the AWS Redshift SQL database, the Bliss tables required splitting the files into smaller chunks and

[42] The "Total # of Unique Rides Trips [sic] with a Reported Incident" had identical values for each month in both the Bliss/Jira Incident Report Classification Data and the Updated Flack Incident Report Classification Data.

uploading them individually into staging tables of 1,000,000 lines or smaller. Once the Bliss staging tables were uploaded into the AWS Redshift SQL database, I combined them back into their original tables.

25. I undertook the following cleaning and standardization steps while loading the data. Those are as follows.

25.1. **Converting Empty (Null) Values**: Within the data, I observed that several formats were used to signify null values within the same dataset (e.g., '\\N', 'N'). I treated all of these as null values.

25.2. **Datetime Formatting**: I converted all datetime values, identified by the presence of the word "timestamp" or "time" in the field, to datetime format, with the exception of the following fields, because they did not include a time value in them:

[redacted]

[redacted]

[redacted]

[redacted]

25.3. **UUID Field Dash Standardization (i.e., "-")**: Uber produced some of its data files with dashes in the UUID fields (e.g., [redacted]), while omitting those dashes in other files. When the files were produced with dashes, I uploaded two versions of the files to "Bucket 2" and the AWS Redshift SQL database: one with dashes and one without. I utilized the version without dashes in my analysis.

25.4. **Unique Identifiers**: I extracted unique identifiers pertaining to Drivers and Riders, following the instructions from Katherine McDonald.[47] I extracted:

[redacted]

[redacted]

[43] See for example: 2100, 0
[44] See for example: 10007_*:*_1_*:*_0_*|*_10740_*:*_2_*:*_675227027, 10007_*:*_1_*:*_0_*|*_10740_*:*_1_*:*_71232, 10007_*:*_1_*:*_0_*|*_10740_*:*_3_*:*_142870478_*|*_10941_*:*_1_*:*_5838426
[45] See for example: 2100, 0
[46] See for example: 3180, 1800, 2160
[47] McDonald 04/25/2025 at 183-184.
[48] McDonald 04/25/2025 at 183.
[49] McDonald 04/25/2025 at 183.

[redacted] [redacted]

[redacted] [redacted]

25.5. **Data Provenance Fields:** I added three fields to assist with data provenance:

25.5.1. "filename": includes the original name of the file as it was produced by Uber

25.5.2. "load_user": identifies which user loaded the table

25.5.3. "load_date": identifies the date the file was uploaded

Flack SA/SM Incident Data

26. Pursuant to Appendix A to Confidentiality Agreement between BDO USA and Plaintiffs' Steering Committee, Uber produced the Flack SA/SM Incident Data into AWS S3 "Bucket 1," which permitted only read access to the data. I downloaded the data from "Bucket 1" using command-line tools executed via Python onto the Amazon Workspace provisioned by BDO.

27. The files were produced as a compressed .zip file, which I extracted in the AWS Secure Environment. Again, using command-line tools executed via Python, I uploaded the data into "Bucket 2" for further processing and analysis. I deleted the .zip file and associated extracted files from the AWS Secure Environment.

28. Within the data, I observed that '\\N' and empty cells were used to signify null values within the dataset. I treated all of these as null values.

28.1. **Data Provenance Fields**: I added three fields to assist with data provenance:

28.1.1. "filename": includes the original name of the file as it was produced by Uber

28.1.2. "load_user": identifies which user loaded the table

28.1.3. "load_date": identifies the date the file was uploaded

28.2. I then loaded all files into the AWS Redshift SQL database using Python.

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[50] McDonald 04/25/2025 at 164.
[51] McDonald 04/25/2025 at 164.

29. To protect the original data, I made a copy of the table, to which I applied the following cleaning and standardization steps. Those are as follows.

29.1. **Datetime Formatting**: I converted all datetime fields ([redacted]) to datetime format.

30. I then added the following fields to facilitate analysis:

30.1. [redacted]**_year:** I created a year variable derived from [redacted].[52]

30.2. **deactivation_flag:** Using the Driver-level data produced in response to Interrogatory No. 16/29, I created a field that identifies whether the [redacted] appears in that production. Drivers appearing in the interrogatory data were assigned a deactivation_flag of 1, and all others were assigned a value of 0.[53]

30.3. **severity_ordered:** Using a reference table constructed from Appendix IV of Uber's 2017-2018 U.S. Safety Report and Appendix III of the 2019-2020 Report, I added a numeric value reflecting the ordered severity of each incident Subcategory.

30.4. **safety_report_category_flag:** I created an indicator denoting whether the incident Subcategory falls within the five publicly disclosed sexual assault and misconduct categories presented in Uber's U.S. Safety Reports.

30.5. **sample_number:** I created a field identifying whether each trip_uuid was included in one of Uber's three sample productions ("sample_1," "sample_2," or "sample_3"). Trips not included in any sample were left null.

30.6. **global_safety_report:** Using the data produced in response to Interrogatory No. 28,[54] I identified trips that appeared in Uber's U.S. Safety Reports and created an indicator variable for those "trip_uuid" values.

30.7. **reported_against_party:** Since Uber did not provide clear testimony regarding the "reported against" fields, I created a unified variable that identifies the party reported against using hierarchical logic derived from the Flack fields list in Todd Gaddis's August 18, 2015 declaration. I first

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[52] Gaddis 11/07/2025 at 97.
[53] See Step 2: Data Validation section for additional analysis of this link.
[54] See Step 2: Data Validation section for additional analysis of this link.

prioritized the [redacted] field, then the [redacted] field, then the [redacted] field, and finally the [redacted] field. When these fields indicated a single party (e.g., Driver, Rider, or Third-Party), I assigned that value. Entries containing multiple values, null values, "UNKNOWN," or "TAXI" were treated as "UNKNOWN." The reported against fields that ended in "v1" or "v2" were not included in the logic as they are deprecated.[55] The query logic is listed below, and the results of that query are in the following table.

```
set reported_against_party = case
    when [redacted] != 'UNKNOWN'
and [redacted] != 'TAXI' then
[redacted]
    when [redacted] != 'UNKNOWN'
then [redacted]
    when [redacted] ilike
'%%DRIVER%%' and [redacted] not
ilike '%%RIDER%%' and [redacted]
not ilike '%%THIRD_PARTY%%' then 'DRIVER'
    when [redacted] ilike
'%%RIDER%%' and [redacted] not
ilike '%%DRIVER%%' and [redacted]
not ilike '%%THIRD_PARTY%%' then 'RIDER'
    when [redacted] ilike
'%%THIRD_PARTY%%' and [redacted]
not ilike '%%RIDER%%' and
[redacted] not ilike '%%DRIVER%%'
then 'THIRD_PARTY'
    when [redacted] ilike
'%%DRIVER%%' and [redacted] not ilike
'%%RIDER%%' and [redacted] not ilike
'%%THIRD_PARTY%%' then 'DRIVER'
    when [redacted] not ilike '%%DRIVER%%'
and [redacted] not ilike
'%%THIRD_PARTY%%' then 'RIDER'
    [redacted] ilike
'%%THIRD_PARTY%%' and [redacted] not
ilike '%%RIDER%%' and [redacted] not
ilike '%%DRIVER%%' then 'THIRD_PARTY'
    else 'UNKNOWN' end;
```

[55] Deposition of Todd Gaddis, 11/07/2025, p. 100.

Table 1: Reported Against Fields
(Source: Updated Flack Incident Report Classification Data, 2013-2024)

[redacted]

30.8. **reported_against_driver_flag**: indicates when the "reported_against_party" was a Driver.

30.9. **driver_reported_against_prior_incident_trip**: indicates whether a trip ([redacted]") occurred after a Driver had a prior SA/SM Incident reported against them ("[redacted]").

31. After completing all data cleaning and variable creation steps, I filtered the dataset to include only incidents with [redacted]_year" between 2017 and 2024,[56] unless otherwise indicated in the analysis.

[56] *See* Footnote 2 in Updated Keller Report for additional information.

Plaintiff Trip and Driver Timeline Data (script: Driver_Profiles_BW.ipynb)

32. Uber produced Driver Trips,[57] Driver Communications,[58] S-RAD Inputs and Scores,[59] and Onboarding/Status Files[60] relating to the Plaintiff Bellwether trips outside of the AWS Secure Environment "Bucket 1." I copied the contents of those files onto the AWS Secure Environment by uploading them to the "Bucket 2" ingress using the web-based upload feature in the Amazon Console.

33. I first loaded all the Driver Trips data for all the Plaintiff Drivers into one table, where matching fields were placed under one another. I then filtered the Driver Trips data to completed trips by including only rows where "Status" is "completed."

34. I added five fields to the Driver Trips data:

34.1. "**begin_trip_hour**": The hour that each trip began, derived from the field native to the dataset [redacted]

34.2. "**day_of_week**": The day of week for each trip, derived from the field native to the dataset [redacted]

34.3. "**year**": The year that each trip occurred, derived from the field native to the dataset [redacted]

34.4. "**unique_id**": A unique identifier for each row in the data based on the order that the data appeared in the table, sorted by [redacted]

34.5. "**day_time_category**": segmented the hours of operation into four categories: Weekend Late Night Hours, Weekday Late Night Hours, Weekend Non-Late Night Hours, and Weekday Non-Late Night Hours.[61]

34.5.1. **Weekend Late Night Hours**: Friday, Saturday, Sunday from 12 AM through 4:59 AM.

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[57] UBER-MDL3084-BW-00006265, UBER-MDL3084-BW-00006254, UBER-MDL3084-BW-00006262 UBER-MDL3084-BW-00006257, UBER-MDL3084-BW-00006259.

[58] UBER-MDL3084-BW-00000012, UBER-MDL3084-BW-00000022, UBER-MDL3084-BW-00000011, UBER-MDL3084-BW-00000029, UBER-MDL3084-BW-00000015.

[59] UBER-MDL3084-BW-00048903, UBER-MDL3084-BW-00048906, UBER-MDL3084-BW-00048905, UBER-MDL3084-BW-00048904.

[60] UBER-MDL3084-BW-00007772, UBER-MDL3084-BW-00012965, UBER-MDL3084-BW-00007742, UBER-MDL3084-BW-00007767, UBER-MDL3084-BW-00007753, UBER-MDL3084-BW-00007778, UBER-MDL3084-BW-00007750, UBER-MDL3084-BW-00007775, UBER-MDL3084-BW-00007745, UBER-MDL3084-BW-00007770.

[61] Deposition of Sunny Wong, 07/23/2025, 29:10-22; Deposition of Sunny Wong, 07/23/2025, 30:12-15

34.5.2. **Weekday Late Night Hours**: Monday, Tuesday, Wednesday, Thursday from 12 AM through 4:59 AM.

34.5.3. **Weekend Non-Late Night Hours**: Friday, Saturday, Sunday from 5:00 AM through 11:59 AM.

34.5.4. **Weekday Non-Late Night Hours**: Monday, Tuesday, Wednesday, Thursday from 5:00 AM through 11:59 AM.

35. I created timeline tables for each Driver, where one line in the data represented one event for that Driver. From the Driver Trips data, I used the request, begin, and dropoff events with the associated status, ratings, and feedback. From the Driver Communications data, I used inbound and outbound message events showing the medium and content. From the -RAD Inputs and Scores, I used S-RAD files for job-level scores and thresholds. From the Onboarding/Status Files I used status and flow information.

36. To this timeline table, I added Bliss Messages, BlissActions, Jira Tickets, Jira Comments, and Interrogatory No. 16/29 Addendum, filtered for records containing the [redacted] or [redacted] associated with the Plaintiff's trips. Where date fields were present without a time component, I assigned a default of 12:00:00 local time to maintain chronological ordering. The final Driver profile tables combined all events into unified chronological timelines and were exported both as individual CSVs for each Driver and in Keller Report - Appendix D1.

Step 2: Data Validation

37. For all files, I started with the standard steps of identifying the size and shape of each file, inspecting the records for missing information (e.g., months, records), and confirmed that fields contained the types of values that would reasonably be expected (e.g., that dates were valid calendar dates).

Interrogatories Nos. 1 through 8 ("Bliss/Jira Incident Report Classification Data," "Flack Incident Report Classification Data," "Updated Flack Incident Report Classification Data" and collectively, "Incident Report Classification")

38. I compared the Bliss/Jira Incident Report Classification Data to the Updated Flack Incident Report Classification Data. There were discrepancies between the counts Uber provided for at least one Subcategory within each monthly Incident Subcategory and for the "Total # of Unique Rides Trips [sic] with a Reported Incident," which I understand to be due to duplication. The "Total # of Completed Rides Trips" had identical values for each month in both the Bliss/Jira Incident

Report Classification Data and the Updated Flack Incident Report Classification Data.

39. I compared the completed trip volume in this dataset against the Weekday/Weekend Trip Volume per State per Year, 2012-2024[62] and found them to be within 1% of one another.

40. I compared the Flack SA/SM Incident Data to the Updated Flack Incident Report Classification Data and found that they agree. By counting the number of unique trip_uuids each month for each Incident Subcategory in the Flack SA/SM Incident Data, I computed the same volume of trips with reported incidents as Uber reported in the Updated Flack Incident Report Classification Data.

Interrogatory No. 28

41. I validated the 12,522 [redacted] values in the first response against the Bliss/Jira SA/SM Incident Data and found all to be present.

42. I validated the 12,522 [redacted] values in the first response against the Flack SA/SM Incident Data and found 57 [redacted] in the Interrogatory No. 28 that were not present in the Flack SA/SM Incident Data.

43. I generally found that the data in the [redacted] to contain numerical data as expected; however, there were some records with data that raised questions, for example, negative values as well as null or zero values in these fields.[63]

Interrogatory No. 16/29 and Interrogatory No. 16/29 Addendum

44. I validated the 207,058 Driver UUID values in the first response against the supplemental response of 40,976 Drivers. All 40,976 Drivers in the supplemental response were in the 207,058 response.

45. I compared the Driver UUID values found in Interrogatory No. 16/29 to Driver UUID values found in the Bliss/Jira SA/SM Incident Data and found no discrepancies.

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[62] Gaddis Exhibit 1574

[63] Those questions were not fully addressed by Uber, including in Uber's June 3, 2025 Defs' Responses to ROG 28 Questions." Therefore, I did not use this data beyond confirming that the number of trips it included match the number of SA/SM Incidents Uber reported in its U.S. Safety Reports. There are analyses pertinent to my opinions that I could perform but, as described in my report, it is more appropriate to conduct my analyses on data that is as complete and accurate as possible. I reserve the right to supplement my analyses pending the outcome of the request for data from Flack, whether or not the additional data is produced.

46. I compared the [redacted] values found in Interrogatory No. 16/29 and the Interrogatory No. 16/29 Addendum to the two [redacted] values [redacted] found in the Flack SA/SM Incident Data and found several discrepancies.

    46.1. There are 4,144 [redacted] from ROG 16/29 that do not appear in the Flack SA/SM Incident Data, using the field [redacted]. All of these were in the Bliss/Jira SA/SM Incident Data.

    46.2. There are 4,130 [redacted] from ROG 16/29 that do not appear in the Flack SA/SM Incident Data, using the field [redacted]. All of these were in the Bliss/Jira SA/SM Incident Data.

    46.3. There are 808 [redacted] from ROG 16/29 Addendum that do not appear in the Flack SA/SM Incident Data, using the field [redacted]. All of these were in the Bliss/Jira SA/SM Incident Data.

    46.4. There are 803 [redacted] from ROG 16/29 Addendum that do not appear in the Flack SA/SM Incident Data, using the field [redacted]. All of these were in the Bliss/Jira SA/SM Incident Data.

Bliss/Jira SA/SM Incident Data

47. I compared the Bliss/Jira SA/SM Incident Data fields and confirmed that I had all the fields that were in the Data Dictionaries.

48. I read in the raw files produced by Uber, and for each field, I counted the number of lines of each value in the field. This allowed me to not only preview the types of data inside the data but also understand the contents of the field. For each field, I also created an output that showed the minimum, average, and maximum values for the values within that field to assist with this review.

49. I examined the data for duplication. The Jira Ticket table had only one [redacted] that was duplicated. Jira Comments, Bliss Messages, and Bliss Actions have significant duplication due to the communication nature of the tables.

50. I reviewed the data for missingness and null values. Within each table, I looked at the number of records and the percentage of records that were missing. I did this analysis across the entire table, also looking by year to look for potential trends in missingness. I identified some missingness in the data, for example:[64]

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[64] This is not intended to be a complete, comprehensive list of every instance of missingness or inconsistency within the data.

50.1. **Before 2017 and after 2022 or Missing Timestamps:**[65] data included trips whose [redacted] appeared to be prior to 2017 or after 2022. The data also included trips where there was data missing from the [redacted].[66]

50.2. **Outside the United States, Ambiguous Location, or Missing Location:**[67] The data included trips whose [redacted] or [redacted][68] listed a location outside of the United States or did not provide sufficient information to confirm that the incident occurred within the United States. There were also trips that apparently occurred in the United States but were missing information sufficient to determine the time zone where the trip occurred.[69]

50.3. **Not a Sexual Assault or Sexual Misconduct Report**: The data included trips where the [redacted] was listed as something other than Sexual Assault or Sexual Misconduct or where no information was provided in the [redacted] field.

50.4. **Missing Trip UUID:** The data included trips where the [redacted] was missing and only [redacted] was available.

50.5. **Conflicting Information**: The data included some trips where, for the same trip, there was conflicting information between the Bliss and Jira systems about the [redacted].

50.6. **Party Reported Against:** The data included trips where it was ambiguous who the party was reported against for a particular trip or ticket, according to the [redacted] field that Uber provided.[70]

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[65] According to Uber, the data was intended to be confined to incidents on trips that occurred between January 1, 2017 and December 31, 2022.

[66] Gaddis 07/11/2025 page 210 line 12; McDonald 04/24/2025 at 120

[67] According to Uber, the data was intended to be confined to incidents on trips that occurred in the United States.

[68] Uber's counsel represented that [redacted] (Mar. 24, 2025 email from J. Haider re: Outstanding safety data issues).

[69] The Bliss/Jira SA/SM Incident Data does not include local time for trips and instead uses UTC. Without sufficient, reliable geographical information, I cannot translate UTC to local time.

[70] Uber represented that Bliss and Jira do not have a field that indicates whether the incident was reported against the Rider, Driver, or another party, for example, in the March. 24, 2025 Field Convenience Description List. To determine the party reported against, Uber instructed to use a field Uber created and populated when it produced the data (the [redacted] field) (Email from Jay Haider on February 1, 2025. However, I noted conflict between the data in the [redacted] field and Uber's representations versus other related fields in the Bliss and Jira data.

Flack SA/SM Incident Data

51. The first production (October 13, 2025) of the Flack SA/SM Incident Data was missing three columns ([redacted]), which Uber later produced on October 17, 2025.

52. I read in the raw files produced by Uber, and for each field, I counted the number of lines of each value in the field. This allowed me to not only preview the types of data inside the data but also understand the contents of the field. For each field, I also created an output that showed the minimum, average, and maximum values for the values within that field to assist with this review.

53. I examined the data for duplication and found none at the [redacted]. However, I found records with the exact same [redacted] and [redacted] within the same city, as well as records with the exact same [redacted] [redacted] and [redacted] combinations, but for different [redacted].

54. I reviewed the data for missingness and null values. Within each table, I examined the number of records and the percentage of missing records. I found there were 416 records with no [redacted] and 405 records where the [redacted] are both blank.

55. I then compared the Flack SA/SM Incident Data to the Bliss/Jira SA/SM Incident Data and noted several discrepancies between those datasets:

    55.1. 11,637 [redacted] in the Bliss/Jira SA/SM Incident Data are not in the Flack SA/SM Incident Data, and 89 Flack (2017-2022) [redacted] are not in the Bliss/Jira SA/SM Incident Data.

    55.2. 158,263 [redacted] in the Bliss/Jira SA/SM Incident Data are not in the Flack SA/SM Incident Data, and 107,158 Flack (2017-2022) [redacted] are not in the Bliss/Jira SA/SM Incident Data.

    55.3. 6,995 [redacted] values in the Bliss/Jira SA/SM Incident Data are not in the Flack SA/SM Incident Data, and 1,547 Flack (2017-2022) [redacted] values are not in the Bliss/Jira SA/SM Incident Data.

    55.4. 7,032 [redacted] values in the Bliss/Jira SA/SM Incident Data are not in the Flack SA/SM Incident Data, and 1,416 Flack (2017-2022) [redacted] values are not in the Bliss/Jira SA/SM Incident Data.

    55.5. I found the following additional inconsistencies:

55.5.1. In 800 reports, the Driver [redacted] differ. In 269 reports, the [redacted] is not.

55.5.2. In 10,098 reports, the Driver [redacted] differ. In 269 reports, the [redacted] is not.

55.5.3. The [redacted] field was Unknown for 67,659 records.

1.1.1. There was disagreement in the values contained within the [redacted] fields[71] for the same [redacted] as shown in Table 1 above. For example, for 208 records, the [redacted] indicated that the party was "DRIVER" while the [redacted] indicated "RIDER".

Plaintiff Trip and Driver Timeline Data

56. I checked that all expected columns were present and populated for each Plaintiff Driver [redacted].

57. Driver Trips,[72] Driver Communications,[73] S-RAD Inputs and Scores,[74] and Onboarding/Status Files[75]

58. I cross-checked the final combined timeline table against the original data sources. I sampled records from the timeline table and confirmed that each event, Driver Trips, Driver Communications, S-RAD Inputs and Scores, Onboarding/Status Files, Bliss Messages, Bliss Actions, Jira Tickets, Jira Comments, Interrogatory No. 16/29 and Interrogatory No. 16/29 Addendum, matched the corresponding entries in the raw files and the AWS Redshift SQL

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[71] dominant_ticket_reported_against_provided_by_agent dominant_ticket_reported_against_inferred_probable, dominant_ticket_reported_against_inferred_possible, all_tickets_reported_against_inferred_possible

[72] UBER-MDL3084-BW-00006265, UBER-MDL3084-BW-00006254, UBER-MDL3084-BW-00006262 UBER-MDL3084-BW-00006257, UBER-MDL3084-BW-00006259.

[73] UBER-MDL3084-BW-00000012, UBER-MDL3084-BW-00000022, UBER-MDL3084-BW-00000011, UBER-MDL3084-BW-00000029, UBER-MDL3084-BW-00000015.

[74] UBER-MDL3084-BW-00048903, UBER-MDL3084-BW-00048906, UBER-MDL3084-BW-00048905, UBER-MDL3084-BW-00048904.

[75] UBER-MDL3084-BW-00007772, UBER-MDL3084-BW-00012965, UBER-MDL3084-BW-00007742, UBER-MDL3084-BW-00007767, UBER-MDL3084-BW-00007753, UBER-MDL3084-BW-00007778, UBER-MDL3084-BW-00007750, UBER-MDL3084-BW-00007775, UBER-MDL3084-BW-00007745, UBER-MDL3084-BW-00007770.

database tables. Finally, I confirmed that the number of records per Driver aligned with the sum of events in the original sources.

Sample Data

2. I checked that all [redacted] from the attachment sampling exercise were included in the Flack SA/SM Incident Data. Two [redacted] were missing.[76]

Step 3: Descriptive Analytics & Visualization

59. For this step, I relied on the reporting scripts to conduct data analysis and generate descriptive analytics. The script systematically produced cross-tabulations and visualizations that highlighted trends and patterns in the data.

Interrogatory No. 28

60. I did not do additional analysis on this dataset. Due to the noted gaps and inconsistencies in this data as previously described, I reserve the right to supplement my analyses pending the outcome of the request, whether or not the additional data is produced.

Interrogatory No. 16/29 and Interrogatory No. 16/29 Addendum

61. I did not do additional analysis on this dataset in the Secure AWS Environment. Due to the noted gaps and inconsistencies in this data as previously described, I reserve the right to supplement my analyses pending the outcome of the request, whether or not the additional data is produced.

Interrogatories Nos. 1 through 8 ("Bliss/Jira Incident Report Classification Data," "Flack Incident Report Classification Data," "Updated Flack Incident Report Classification Data" and collectively, "Incident Report Classification")

62. For the Bliss/Jira Incident Report Classification Data, I aggregated the "Total # of Unique Rides Trips [sic] with a Reported Incident" to the month and again to the year to provide monthly and annual totals.

63. For the Updated Flack Incident Report Classification Data, which Uber said was deduplicated, I aggregate the data to the month and again to the year to provide monthly and annual totals. I verified that my totals matched the "Total # of Unique Rides Trips with a Reported SA/SM Incident Based on the Dominant Ticket."

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[76] [redacted] c30284a54877409196ee94ef83529ad0, 112d69894f2c4d5c92865a4441f7da6e

64. The results of my analyses are shown in my report, and the code has been disclosed in the script Main_Report.ipynb.

Bliss/Jira SA/SM Incident Data

65. I did not do additional analysis on this dataset. There are analyses pertinent to my opinions that I could perform and, as described in my report, it is more appropriate to conduct my analyses on data that is as complete and accurate as possible. I reserve the right to supplement my analyses pending the outcome of the request for data from Flack, whether or not the additional data is produced.

Updated Flack Incident Report Classification Data

66. For the Updated Flack Incident Report Classification Data, which Uber said was deduplicated, I aggregate the data to the month and again to the year to provide monthly and annual totals. I verified that my totals matched the "Total # of Unique Rides Trips with a Reported SA/SM Incident Based on the Dominant Ticket."

67. The results of my analyses are shown in my report and the code has been disclosed in the script Main_Report.ipynb.

Plaintiff Trip and Driver Timeline Data

68. For the Driver profiles, I analyzed trip prevalence on specific days of the week and times of day, Driver ratings, and the frequency of car idle nudges.

69. The results of my analyses are shown in my report and the code has been disclosed in the script Driver_Profiles_BW.ipynb.

Step 4: Automation

70. All of my steps for all datasets are fully automated, streamlining data handling and analysis throughout the entire workflow and allowing for reproducibility. The code that I used aligns to the core tenets of Data Science.

71. All SQL and Python scripts were written with clear comments and organization, supported by a README file that outlines the order in which scripts should be executed. This approach not only automates routine processes such as data cleaning, transformation, and aggregation but also guarantees that analyses can be reproduced consistently across environments and data volumes. By combining automation with documentation, including specifically this

Methodology, I provide a clear account of how conclusions were reached that enables replication.

72. For Defendants' convenience, I have disclosed through "Bucket 1m" the code underlying the analyses in my report and associated data that I or my team uploaded into the "Bucket 2" ingress. These offloads are timestamped and cannot be deleted by Plaintiffs. Pursuant to the agreement between Uber and Plaintiffs' Counsel, I am not re-producing data that Uber had uploaded in "Bucket 1" back to Uber through "Bucket 1m," including the Bliss/Jira SA/SM Incident Data, Interrogatory No. 28, Interrogatory No. 16/29, and Interrogatory No. 16/29 Addendum.

IV. Document Review

73. I also reviewed documents provided via Everlaw, including depositions, exhibits, and internal Uber documents. I identified relevant documents by searching the platform for terms that applied to the data I analyzed or to specific Bellwether Plaintiff trips, including for the purposes of Driver Profiles (see Keller Report - Appendix D). The search terms that I used originated from deposition testimony, exhibit references, or documents that related to the data I analyzed. This process allowed me to connect the data produced with records describing how that was generated and used by Uber. I gave the greatest consideration to materials that were consistent with both deposition testimony and findings from analyses. At times, I was also provided documents by Plaintiff's Counsel, including documents produced in relation to the five Bellwether Plaintiff Drivers. The Bates numbers for all documents that I reviewed are included in Keller Report - Appendix G.

V. Maintenance of Standards and Controls

74. I took multiple steps to confirm that my analyses in this matter were accurate, reproducible, and consistent with the underlying data and documentation. I validated key data Transformations with targeted queries that could be independently reproduced. I cross-checked outputs against the source data and metadata to confirm that counts, distributions, and field mappings were consistent. As part of my checks:

74.1. For each file that I moved from "Bucket 2" to the AWS Redshift SQL database, I confirmed that the length of the original file was the length of the file that was uploaded to the AWS Redshift SQL database.

74.2. When loading the data into the AWS Redshift SQL database, I confirmed that the original count of records matched the loaded count.

74.3. Checked for explosions in the data for unexpected surges in counts or duplicated records that would suggest errors in joins or transformations.

74.4. Performed spot checks and sampling of individual records to verify that the raw data corresponded correctly to the processed results.

75. These quality-control measures reflect standard best practices I apply in all of my expert analyses and provide confidence that my findings are based on accurate and reliable data.

VI. Known or Potential Rate of Error

76. The analyses in this report are based on straightforward counting and summing of records. As such, the potential rate of error is limited to the issues identified in the Validation section above, which are largely de minimis or do not impact my analysis because I do not rely on those fields. The results reflect the true volumes of records as produced. Importantly, no extrapolation, statistical modeling, or sampling was conducted in this matter. All outputs are direct tabulations from the Final Summary Table and are therefore reproducible by re-running the same queries.

VII. Objectivity of Analysis and Assumptions

77. My analysis is based on industry-standard, replicable methods and techniques. I wrote all queries and analyses to yield unbiased, objective results. I fully disclosed all data and documents produced by Defendants and provided to me in this matter. I employed these measures to ensure that my analysis is free from subjectivity and is reproducible and transparent. I assumed for my analysis that the data and documents produced by Uber were truthful and accurate as represented.

IN THE UNITED STATES COURT
FOR THE NORTHERN DISTRICT OF CALIFORNIA

In re. Uber Technologies, INC., Passenger Sexual Assault Litigation	Case No. 3:23-md-03084-CRB

Updated Expert Report of Lacey R. Keller ("Updated Keller Report")
Appendix B - Definitions

Dated: December 2, 2025

Confidential and Subject to Protective Order

1. **All Reported Parties:** This term refers to all SA/SM Incident reports made against Drivers, Riders, Third-Parties, or where the incident is considered unknown (i.e., when the field is blank or carries a value of 'UNKNOWN', 'TAXI', or none of Uber's inferred fields identify a single, exclusive party).

2. **Bellwether Plaintiffs:** I use this term to refer to the Plaintiffs in this matter at the time of this report who reported the SA/SM Incidents against the Uber Drivers detailed in Keller Report - Appendix D.

3. **COVID:** This term refers to the "Global Pandemic" declared by the World Health Organization on March 11th, 2020 through May 5th, 2023, referring to an outbreak of the infectious disease Coronavirus 2019 (colloquially known as COVID).[1] In some images in my main report, there are shaded grey boundaries that reflect the mask policy implemented by Uber during that time.[2]

4. **Incident Category**: This term refers to either "Sexual Assault," "Sexual Misconduct," or both, as defined in Uber's U.S. Safety Report 2021-2022 Appendix I:[3]

   4.1. **Sexual Assault ("SA"):** Uber uses this term to refer to "any physical or attempted physical contact that is reported to be sexual in nature and without consent. This can include incidents within the taxonomy ranging from attempted touching of a non-sexual body part (for example, a user trying to touch a person's shoulder in a sexual/romantic way) to non-consensual sexual penetration."[4]

   4.2. **Sexual Misconduct ("SM")**: Uber uses this term to refer to "non-physical conduct (verbal or staring) of a sexual nature that happens without consent or has the effect of threatening or intimidating the person against whom such conduct is directed. This can include incidents within the taxonomy ranging from staring/leering to verbal threat of sexual assault."[5]

   4.3. **"SA/SM":** Uber uses this abbreviation to refer to Sexual Assault and Sexual Misconduct, an overarching categorization that includes all Sexual Assault and Sexual Misconduct Incidents. "SA/SM" is used in this report consistent with Uber's use of the term.

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[1] "Coronavirus disease (COVID-19) pandemic", World Health Organization, https://www.who.int/europe/emergencies/situations/covid-19.
[2] https://www.uber.com/blog/your-safety-during-the-new-normal/; https://www.uber.com/blog/changes-to-mask-requirements-and-covid-19-policies/
[3] Deposition of Frank Chang, p. 24, Exhibit 751.
[4] Deposition of Sunny Wong, 4/16/2025, p. 5, Exhibit 2801.
[5] Deposition of Sunny Wong, 4/16/2025, p. 5, Exhibit 2801.

5. **Incident Subcategory or Subcategory**: Uber's U.S. Safety Report 2017-2018 Appendix IV and 2019-2020 Appendix III defines the following 21 subcategories of Sexual Assault and Sexual Misconduct reports,[6] also known as the "taxonomy:"[7]

   5.1. **Attempted Kissing of a Non-Sexual Body Part**: Someone attempted to kiss, lick, or bite, but did not come into contact with, any non-sexual body part (hand, leg, thigh) of the user, and the user perceived the attempt to be sexual.

   5.2. **Attempted Kissing of a Sexual Body Part**: Someone attempted to kiss, lick, or bite, but did not come into contact with the mouth, breast(s), buttock(s), or genitalia of the user, and the user perceived the attempt to be sexual.

   5.3. **Attempted Non-Consensual Sexual Penetration ("Attempted Rape"):** Without explicit consent from a user, someone attempted to penetrate the vagina or anus of a user with any body part or object. Any attempted removal of another person's clothing to attempt to access a sexual body part will be classified as Attempted Non-Consensual Sexual Penetration. This also includes attempted penetration of the user's mouth with a sexual organ or sexual body part; however, it excludes kissing with tongue or attempts to kiss with tongue.

   5.4. **Attempted Touching of a Non-Sexual Body Part**: Someone attempted to touch, but did not come into contact with, any non-sexual body part (hand, leg, thigh) of the user, and the user perceived the attempt to be sexual.

   5.5. **Attempted Touching of a Sexual Body Part**: Someone attempted to touch, but did not come into contact with, any sexual body part (mouth, breast(s), buttock(s), or genitalia) of the user, and the user perceived the attempt to be sexual.

   5.6. **Comments or Gestures - Asking Personal Questions**: Someone asks specific, probing, and personal questions of the user. This would include questions about the user's personal life, home address, contact information (e.g., phone, email, social media), romantic or sexual preferences.

   5.7. **Comments or Gestures - Comments About Appearance**: Someone makes uncomfortable comments on the user's appearance. This includes both disparaging and complimentary comments.

   5.8. **Comments or Gestures - Explicit Comments:** Someone described or represented sexual activity or body parts in a graphic fashion.

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[6] McDonald Deposition 04/25/2025, p. 205; Deposition of Katherine McDonald, 4/25/2025, 205-206.
[7] Deposition of Frank Chang, Exhibit 749; Deposition of Frank Chang, Exhibit 751; Deposition of Frank Chang, Exhibit 750; Deposition of Katherine McDonald,04/25/2025, p. 205; Deposition of Katherine McDonald, 4/25/2025, p. 205-206.

5.9. **Comments or Gestures - Explicit Gestures**: Someone made sexually suggestive gestures at the user.

5.10. **Comments or Gestures - Flirting**: Someone makes verbally suggestive comments to the user about engaging in romantic or non-romantic activities. This also includes non-verbal, suggestive flirting, including becoming physically close to a person in a way the user felt was sexual or flirtatious.

5.11. **Displaying Indecent Material**: Indecent material, including pornography or other sexual images, was seen by the user.

5.12. **Indecent Photography/Video Without Consent**: Someone has taken, without consent, an inappropriate photograph of a user's sexual body part (e.g., down shirt, up skirt, etc.).

5.13. **Masturbation/Indecent Exposure**: Someone has exposed genitalia and/or is engaging in sexual acts in the presence of a user. This excludes public urination where no sexual body part (buttock, penis, breast) was exposed.[8]

5.14. **Non-Consensual Sexual Penetration ("Rape"):** Without explicit consent from a user, someone penetrated, no matter how slight, the vagina or anus of a user with any body part or object. This includes penetration of the user's mouth with a sexual organ or sexual body part. This excludes kissing with tongue.

5.15. **Non-Consensual Kissing of a Sexual Body Part**: Without consent from the user, someone kissed or forced a kiss on either the breast or buttocks of the user. This would include kissing on the lips or kissing while using tongue.

5.16. **Non-Consensual Kissing of a Non-Sexual Body Part:** Without consent from the user, someone kissed, licked, or bit, or forced a kiss, lick, or bite on any non-sexual body part (hand, leg, thigh) of the user.

5.17. **Non-Consensual Touching of a Sexual Body Part:** Without explicit consent from the user, someone touched or forced a touch on any sexual body part (breast, genitalia, mouth, buttocks) of the user.

[8] In Updated Flack Incident Report Classification Data, Flack Incident Report Classification Data, and Flack SA/SM Incident Data, this Masturbation is its own Subcategory and Self Touching/Indecent Exposure is its own Subcategory. In Bliss/Jira SA/SM Incident Data and Bliss/Jira Incident Report Classification Data, Masturbation is its own Subcategory, Masturbation/Indecent Exposure is its own Subcategory, and Self Touching/Indecent Exposure is its own Subcategory. Uber's Appendix IV from its U.S. Safety Reports provides Masturbation/Indecent Exposure as the Subcategory. *See also* Deposition of Katherine McDonald, 10/7/2024, p. 130-131.

5.18. **Non-Consensual Touching of a Non-Sexual Body Part:** Without explicit consent from the user, someone touched or forced a touch on any non-sexual body part (hand, leg, thigh) of the user.

5.19. **Staring or Leering:** Someone gazes at a user in an unpleasant, uncomfortable, prolonged, or sexual manner. Staring or leering is constant and unwavering. This includes viewing both sexual and non-sexual body parts.

5.20. **Soliciting a Sexual Act:** Someone directly asks for a kiss, displays of nudity, sex, or contact with a sexual body part (breast, buttock, genitals). This could be a direct solicitation or a solicitation in exchange for money or favors.

5.21. **Verbal Threat of Sexual Assault:** Someone directed verbal explicit/direct threats of sexual violence at a user.

6. Uber categorizes some SA/SM Incidents as "Insufficient Information" or "Parent Category Use Tracking" in the "Incident Subcategory" field in the Incident Report Classification data. As used herein, these terms mean:

6.1.1. **Insufficient Information:** SA/SM Incidents reports for which Uber did not have enough details to classify the incident.[9]

6.1.2. **Parent Category Use Tracking:** SA/SM Incidents that are categorized only as "Sexual Assault" or "Sexual Misconduct" but not further categorized into a subcategory.[10]

7. **Opposite Gender Pairings:** I use this term to refer to Uber matches where the Driver gender was male and the Rider gender was female, or the inverse (Driver gender was female and Rider gender was male).

8. **Safety Report Subcategories:** I use this term to refer to the five categories of SA/SM Incidents that Uber included in Uber's U.S. Safety Reports. Those categories are:

8.1. Sexual Assault: Non-Consensual Sexual Penetration

8.2. Sexual Assault: Non-Consensual Kissing - Sexual Body Part

8.3. Sexual Assault: Non-Consensual Touching - Sexual Body Part

8.4. Sexual Assault: Attempted Non-Consensual Sexual Penetration

8.5. Sexual Assault: Non-Consensual Kissing - Non-Sexual Body Part

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[9] Deposition of Todd Gaddis, 07/11/2025, p. 78.
[10] Deposition of Todd Gaddis, 07/11/2025, p. 81-82.

9. **Sexual Assault and Sexual Misconduct Incidents or SA/SM Incidents:** I use these terms interchangeably to refer an Uber-related incident report of an unwanted sexual experience (as defined by Uber in its U.S. Safety Report 2017-2018, pp. 15-16). Every time I refer to SA/SM Incidents, I am only referring to SA/SM Incidents that Uber represented were reported in the United States.

10. **Third Parties:** I use this term to refer to any individual who may have reported an SA/SM Incident to Uber but who was not necessarily involved in the SA/SM Incident.[11]

11. **User:** I use this term to refer to a person who interacts with the Uber platform as a Driver or a Rider.

12. **Weekend Late Night:** I use this term to refer to Friday from 12 A.M. to 4:59 AM, Saturday from 12 A.M. to 4:59 A.M., and Sunday from 12 A.M. to 4:59 A.M.[12]

[11] UBER_JCCP_MDL_003633406.
[12] Deposition of Sunny Wong, 07/23/2025, 29:10-22; Deposition of Sunny Wong, 07/23/2025, 30:12-15.

IN THE UNITED STATES COURT

FOR THE NORTHERN DISTRICT OF CALIFORNIA

In re. Uber Technologies, INC., Passenger Sexual Assault Litigation	Case No. 3:23-md-03084-CRB

Updated Expert Report of Lacey R. Keller ("Updated Keller Report") Appendix C - Qualifications and Remuneration

Dated: December 2, 2025

Confidential and Subject to Protective Order

Table of Contents

I. Qualifications

1. I am the co-owner of MK Analytics, Inc. (MKA), a firm I co-founded with Meredith McCarron in 2021. MKA specializes in creating tailored platforms and reports that integrate disparate data and provide actionable insights for clients in the not-for-profit, government, and private sectors. MKA has established itself as a trusted partner for nationally known non-profit organizations, the United States federal government, several state attorneys general, local government, and some of the country's largest plaintiffs' law firms.

2. I am an Adjunct Professor at Washburn University School of Business in the data science department, where I co-teach the capstone project course and solo lecturer for the introductory course to data information systems, analysis, and database management.

3. Prior to founding MK Analytics, I was the Managing Director for Data Mining & Analytics with Gryphon Strategies, Inc. I was hired to create and direct their data mining and analytics division. This division advised financial and law firms on leveraging data for investments and investigations.

4. Prior to founding Gryphon Strategies' Data Mining & Analytics division, I founded and directed the Research and Analytics Department for the New York State Office of the Attorney General (NYS OAG) from 2013 to 2017. As a result of my leadership, the NYS OAG became the first state office attorney general to hire a data scientist. I grew my staff from one research assistant to seven full-time staff.

5. I have also worked in various research and analytical positions, including the research department of the Service Employees International Union (SEIU) 32BJ, the largest property services union in the country. I was also a researcher for the Global Clearinghouse and a Teaching Assistant at the New School for Social Research. As a consultant, I have been hired by and have provided pro-bono assistance to many state and federal agencies as well as nonprofits on the use of data mining and analytics in investigations.

6. The work I have done throughout my career relates directly to the analysis undertaken in this report. Specifically, I have developed a specialty in compiling and analyzing disorganized and disparate data. My work over the past 15 years has required me to extract, process, clean, merge, and analyze both public and confidential data, which often comes poorly formatted and from disparate locations. From these convoluted datasets, I have identified trends and outliers that have furthered investigations or prosecutions.

7. Since 2019, I have served as an expert witness in data mining and analytics for the National Prescription Opiate Litigation and related trials, providing comprehensive analyses on annual, geographic, and market trends, identifying outlier activities, and implementing compliance metrics and red flags. With 20 depositions and six trial

testimonies in this litigation, my expertise was never limited or excluded. The analyses I provided in these matters drew upon my unique and specialized skill set that has been developed over a decade of research and analytical experience.

8. I was often tasked with identifying instances of wrongdoing by companies. For example, while at SEIU 32BJ, I reviewed public records for data to identify wrongdoing by cleaning companies and cleaning contractors around the country. Through thorough research and documentation, I was able to identify a cleaning company that was creating shell companies to keep a small business cleaning contract at the Walter Reed Medical Center. SEIU 32BJ submitted this information to the General Services Administration. To the best of my knowledge, that company or its subsidiaries/affiliates lost the contract for that site.

9. My primary directive when the NYS OAG hired me was to help the office identify areas for investigation using data. I often would use public data to assist with these investigations. For instance, I combined publicly available tax assessor, mortgage records, and real estate listings to identify hundreds of landowners potentially out of compliance with the city's 421-a tax benefit program that the NYS OAG investigated resulting in hundreds of thousands of dollars in settlements with landlords.

10. My work over the past 15 years has required me to extract, process, clean, merge, and analyze both public and confidential data, which often comes poorly formatted and from disparate locations. From these convoluted datasets, I have identified trends and outliers that have furthered investigations or prosecutions.

11. While at the NYS OAG, I developed and managed the Community Overdose Prevention (COP) Program to use data analytics to determine how best to deploy life-saving naloxone across law enforcement officers statewide. Under that program, I oversaw the collection of information related to naloxone disbursements, which jumpstarted tracking opioid overdoses more efficiently throughout the state. I used the data I collected, as well as external datasets, to deepen my understanding of opioid usage in New York State.

12. I have written or co-authored numerous public-facing reports using my data analysis to advance a variety of investigations into illegal activity, many of which have been covered by national media outlets. For instance, my analysis published in a report issued by the NYS OAG helped reveal Airbnb's illegal activity in New York City.[1] In addition, while at SEIU 32BJ, I authored two papers about the physical building conditions of New York City public school facilities,[2] the second of which was widely covered by local news and prompted a city council oversight hearing to address the issues raised.

13. In my work, I have frequently received productions of data in a format not initially conducive to analysis, such as productions containing PDF versions of spreadsheets or thousands of files of various formats. In a case that settled for hundreds of millions of dollars, I supervised the team that identified and extracted information about shipments

[1] https://ag.ny.gov/sites/default/files/reports/AIRBNB_REPORT.pdf
[2] https://assets1.cbsnewsstatic.com/i/cbslocal/wp-content/uploads/sites/14578484/2013/05/falling-further-apart1.pdf

from the distributors' production in that case. Because of this analysis, my team and I were able to detect millions of improper shipments made in New York State that were then used by NYS OAG attorneys in court and ultimately led to the judge ordering the defendant in that case to pay almost $250 million in damages.

14. My experience also includes processing very disorganized data produced by defendants in various cases for investigations and prosecution. For a wage theft case brought by the NYS OAG, I was asked to identify instances of an employer "stealing time" from employees. To complete this analysis, I had to extract information from thousands of PDF employee timecards to extrapolate and identify instances of missing time. Based on my analysis, I determined that over $500,000 was owed to employees.

15. In my work, I supervise complicated data management and analysis. For an NYS OAG investigation into posting fake trades in emerging market foreign exchange currency options, I used scripts to extract relevant trade information from two years of instant message, email, and voice communications between brokers. Working with my team, I then compared the relevant information from postings to the trade confirmations of completed trades brokered to determine which trades were real and which were fabricated. This analysis was relied upon to generate a criminal complaint filed by the NYS OAG. The firms ultimately pled guilty to one count of securities fraud.

16. I am also experienced in working with vast amounts of sensitive information. In developing the interactive dashboard on illegal gun trafficking in New York, the NYS OAG obtained the anonymized and highly confidential firearms tracing data from the Bureau of Alcohol, Tobacco, Firearms and Explosives. My team and I were authorized by dozens of police departments to access their firearms trace data. I transformed that data into an interactive tool used by New York State law enforcement agencies to identify potential firearms trafficking based on relevant analytics. This data required considerable cleaning and analysis, including geocoding and entity resolution to identify the same firearm purchaser that relied on different aliases, addresses, and other biographical information to avoid detection. The publication of the dashboard and report "Target on Trafficking: New York Crime Gun Analysis" earned a front-page feature in the New York Daily News and was later cited by the Journal of Urban Health, Data-Smart City Solutions, the American Medical Association, and the Rockefeller Institute.

17. I am frequently called upon to analyze very large data. While working on investigations of broadband internet investigations at the NYS OAG, I collected public speed test data and submissions to the Office made by the general public about the download speed. This preliminary analysis was the basis for opening an investigation into the practices of the largest broadband providers regarding the internet speeds of their customers. As part of this investigation, I drafted the data request to broadband providers for the account and other relevant information that would impact a customer's internet speed. I connected several datasets totaling hundreds of millions of records, including the customer account data (what internet tier they were provisioned), the internet speed test results, as well as information about the modem/router configuration. The results of my

analysis and the analysis that I supervised were used in the complaint the NYS OAG filed against Time Warner Cable. The case ultimately settled for $174.2 million.

18. I have also been requested to develop dashboards that allow end-users to explore the data in their investigation or litigation. I developed an interactive dashboard as part of an expert report regarding contamination of the water systems serving members of the military and civilians living near the Red Hill Bulk Storage Facility in Honolulu, Hawaii. I also worked alongside and supervised the team that developed interactive maps that showed the fire progression against emergency response, road closures, public safety, telecommunications, and other relevant data over time to better understand the impact of a wildfire on a specific geographic area. I also developed and consulted on data integration and visualization tools for gun violence and firearm manufacturing for Everytown for Gun Safety, the country's largest gun violence prevention organization.

19. I received the NYS OAG's Innovation in Law Enforcement Award for my work on gun trafficking and twice received the NYS OAG's Superior Service Award.

20. I was a member of the 28th Class of Coro's Leadership New York and was part of City and State's 40 Under 40 Rising Stars in 2016.

21. I hold a Master of Arts in Economics from the New School and a Bachelor of Business Administration from Washburn University.

I. Deposition and Trial Testimony

22. I have been deposed on the following matters:

    22.1. June 13, 2019, after filing an expert analysis with the Track One MDL 2804 Opiate Litigation.

    22.2. January 23, 2020, after filing an expert analysis for the Opioid Litigation, 400000/2017 Relating to Case Nos. County of Suffolk, 400001/2017; County of Nassau, 400008/2017; and New York State, 400016/2018.

    22.3. March 6, 2020, after filing an expert analysis for Staubus, et al, v. Purdue Pharma, L.P., et al, Case No. C-41916.

    22.4. September 18, 2020, after filing an expert analysis for the Opioid Litigation, No. 3:17-cv-1362 (S.D.W.Va.) and No. 3:17-cv-1665 (S.D.W.Va.).

    22.5. February 23, 2021, after filing an expert analysis for The People of the State of California v. Purdue Pharma L.P., et al. Case No. 30-2014-00725287-CU-BT-CXC.

    22.6. May 27, 2021, after filing an expert analysis for State of New Hampshire v. Johnson & Johnson, et al. Docket No. 217-2018-CV-0067.

22.7. June 23, 2021, after filing an expert analysis for State of Washington v. McKesson Corporation, Cardinal Health Inc., and AmerisourceBergen Drug Corporation, Case #19-2-06975-9 SEA.

22.8. August 18, 2021, after filing an expert analysis for State of Rhode Island vs. Purdue Pharma L.P., et al, PC No. 2018-4555.

22.9. August 31, 2021, after filing an expert analysis for Re: Texas Opioid Litigation, No. 2018-63587.

22.10. December 29, 2021, as a 30(b)(6) witness in the State of Rhode Island vs. Purdue Pharma L.P., et al, PC No. 2018-4555.

22.11. January 6, 2022, after filing an expert analysis for The City and County of San Francisco, California vs. Purdue Pharma L.P., et al, PC No. 3:18-cv-07591-CRB.

22.12. February 16, 2022, after filing an expert analysis for In the Circuit Court of Kanawha County, West Virginia, in re: Opioid Litigation, Civil Action No. 21-C-9000 MFR State of West Virginia Opioid Manufacturer Proceedings.

22.13. April 25, 2022, after filing an expert analysis for In the Circuit Court of Kanawha County, West Virginia, in re: Opioid Litigation, Civil Action No. 21-C-9000 MFR State of West Virginia Opioid Manufacturer Proceedings.

22.14. May 9, 2022, after filing an expert analysis for State of New Mexico vs. Purdue Pharma L.P., et al No. D-101-CV-2017-02541.

22.15. September 7, 2022, after filing an expert analysis for In the Circuit Court of Kanawha County, West Virginia in re: Opioid Litigation, Civil Action #21-C-9000 PHARM.

22.16. November 16, 2022, after filing an expert analysis for The Montgomery County Board of County Commissioners, et al. v Cardinal Health Inc. et al., Case No 1:18-op-46326-DAP.

22.17. December 13, 2022, after filing an expert analysis for the State of Michigan in the Circuit Court for the County of Wayne in re: Opioid Litigation, 19-016896-NZ.

22.18. April 10, 2023, after filing an expert analysis in The Circuit Court of Kanawha County, West Virginia in re: Opioid Litigation Civil Action No.21-C-9000 Pharm.

22.19. October 18, 2023, after filing an expert analysis in Patrick Feindt, Jr et al. v. The United States of America, Civil No. 1:22-cv-397-LEK-KJM in the United States District Court for the District of Hawaii.

22.20. April 8, 2024, after filing an expert analysis in Holwill v. AbbVie Inc. et al 1:18-cv-06790 in the United States District Court Northern District of Illinois.

22.21. May 23, 2024, after filing expert analyses in re: National Prescription Opiate Litigation "Track Eight Cases" Case No. 17-md-2804 and in re: National Prescription Opiate Litigation No. 17-md-2804 PHARM in the Circuit Court of Tarrant County, Texas.

22.22. March 27, 2025, after filing expert analyses in Alanna Dunn, et al v Cuyahoga County et al Case No. 1:23-cv-00364 in the United States District Court Northern District of Ohio Eastern Division.

22.23. October 27, 2025, after filing expert analyses in re. Uber Technologies, INC., Passenger Sexual Assault Litigation Case No. 3:23-md-03084-CRB in the United States District Court Northern District of California.

23. I have provided the following testimony for trial:

23.1. May 4 and May 5, 2021, after filing an expert analysis for The People of the State of California v. Purdue Pharma L.P., et al. Case No. 30-2014-00725287-CU-BT-CXC.

23.2. June 15, 2021, after filing an expert analysis for the Opioid Litigation, No. 3:17-cv-1362 (S.D.W.Va.) and No. 3:17-cv-1665 (S.D.W.Va.).

23.3. December 7-9, 2021, after filing an expert analysis for State of Washington v. McKesson Corporation, Cardinal Health Inc., and AmerisourceBergen Drug Corporation, Case #19-2-06975-9 SEA.

23.4. April 21 and April 27, 2022, after filing an expert analysis in the Circuit Court of Kanawha County, West Virginia, in re: Opioid Litigation, Civil Action No. 21-C-9000 MFR State of West Virginia Opioid Manufacturer Proceedings.

23.5. June 1, 2022, after filing an expert analysis for The City and County of San Francisco, California vs. Purdue Pharma L.P., et al., PC No. 3:18-cv-07591-CRB.

23.6. September 13, 2022, after filing an expert analysis in the State of New Mexico vs. Purdue Pharma L.P., et al. No. D-101-CV-2017-02541.

23.7. April 29, 2024, after filing an expert analysis in Patrick Feindt, Jr et al. v. The United States of America, Civil No. 1:22-cv-397-LEK-KJM in the United States District Court for the District of Hawaii.

24. I have filed a declaration in the following matters:

24.1. May 27, 2022, after filing an expert analysis for The City and County of San Francisco, California vs. Purdue Pharma L.P., et al, PC No. 3:18-cv-07591-CRB.

24.2. December 21, 2023, in Council et al v. Ivey et al Case No. 2:2023cv00712.

24.3. April 8, 2024, after filing an expert analysis in Patrick Feindt, Jr et al. v. The United States of America, Civil No. 1:22-cv-397-LEK-KJM (D. Haw.) (Federal Tort Claims Act).

24.4. April 25, 2024, in Cayce Collins Moore v. State of Alabama Case No. CC-1986-000003.64.

24.5. January 2025, Alanna Dunn et al v. Cuyahoga County et al Case No. 1:23-cv-00364.

II. Speaking Engagements and Publications

25. I was an invited speaker at the following conferences:

25.1. From Code to Culture: Real Strategies From Women Shaping The Future of AI (2025)

25.2. American Chemical Society (2025)

25.3. Denver Association of Certified Fraud Examiners (ACFE) Annual Conference (2024)

25.4. Maryland ACFE Annual Conference (2024)

25.5. Guest Lecturer at Washburn University School of Business (2018, 2020, 2021, 2022, 2023, 2024)

25.6. Guest Lecturer at Brooklyn Law School (2024)

25.7. Guest Lecturer at Columbia Law School (2024)

25.8. Guest Lecturer at Yale Law School (2022, 2023)

25.9. Association of Certified Fraud Examiners (ACFE) Global Fraud Conference (2019, 2020, 2023)

25.10. American Accounting Association Annual Meeting (2021)

25.11. NASAA Investment Adviser Training (2017, 2019, 2020, 2021)

25.12. Association of Certified Fraud Examiners (ACFE) Law Enforcement and Government Anti-Fraud Summit (2018, 2019)

25.13. Guest Lecturer at the University of Missouri School of Accountancy (2018, 2019)

25.14. PLI Hedge Fund and Private Equity Enforcement & Regulatory Developments 2018 (2018)

26. I have authored or co-authored the following publications:

26.1. Turkington, Victoria; Kahn, Yasha; Keller, Lacey; Hamilton, Ava; Willis, John; Utech, Hailey; Toth, Jamie; Rawson, Jeff. "Market audits combat cannabis misinformation." Journal of Testing and Evaluation (2024).

26.2. Keller, Lacey and Erik Halvorsen. "How Text Mining Can Be Used to Detect Fraud." Fraud Intelligence (2023).

26.3. Keller, Lacey and Eli Nelson. "Using Data in Litigation." Bloomberg Law: Professional Perspective (2022).

26.4. Keller, Lacey and Eli Nelson. "Structured Data." Bloomberg Law: Professional Perspective (2022).

26.5. Keller, Lacey and Eli Nelson. "Structured Data in Discovery." Bloomberg Law: Professional Perspective (2022).

26.6. Keller, Lacey and Eli Nelson. "Using Data in Litigation." Bloomberg Law: Professional Perspective (2022).

26.7. Keller, Lacey and Eli Nelson. "Glossary of Data Terms." Bloomberg Law: Professional Perspective (2022).

26.8. Keller, Lacey and Eli Nelson. "Requesting Data." Bloomberg Law: Professional Perspective (2022).

26.9. Keller, Lacey and Eli Nelson. "Requesting Data." Bloomberg Law: Professional Perspective (2022).

26.10. Keller, Lacey. "Leveraging Traditional and Alternative Data in Investigations." Association of Certified Fraud Examiners Annual Global Fraud Conference (2019).

26.11. Yang, Xitong & McCarron, Meredith & Keller, Lacey & Luo, Jiebo "Tracking Illicit Drug Dealing and Abuse on Instagram Using Multimodal Analysis." ACM Transactions on Intelligent Systems and Technology (2016).

27. I am being compensated at $584.00 per hour for my services in this litigation. Other MK Analytics employees assisted me in my analysis, who are being compensated at rates of $333 to $584 per hour. I am also being reimbursed for all reasonable expenses incurred for my work on this litigation. No part of my compensation is contingent upon the outcome of this litigation, and I have no interest in the litigation or with either party.

LACEY R.KELLER

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EXPERIENCE

Co-Owner and Founder
MK Analytics, Inc.
New York, NY (Feb. 2021 – Present)

Managing Director
Gryphon Strategies
New York, NY (Nov. 2017 – Feb. 2021)

- Led the development of Gryphon Strategies' newest business offering - Data Mining & Analytics to support due diligence cases, fraud investigations, and litigation engagements.

Director of Research & Analytics
New York State Office of the Attorney General
New York, NY (Oct. 2013 – Nov. 2017)

- Built the Attorney General's Research & Analytics department – growing from one research assistant to seven full-time staff – including making the New York Attorney General the first in the country to employ a data scientist. This team supports the office's major initiatives and investigations through open source intelligence research, big data analysis, and data science techniques.
- Managed the redesign and relaunch of the Attorney General's open data and transparency website, NYOpengovernment.com.
- Co-developed the first-of-its-kind report and interactive dashboard on illegal gun trafficking in New York, which was the cover story of the Daily News.
- Provided analysis for the lawsuit against Spectrum-Time Warner Cable and Charter Communications for allegedly defrauding New Yorkers over internet speeds and performance, which was the cover story of the Daily News.
- Co-authored and provided the analysis for the report on illegal Airbnb rental activity in New York City, which was a cover story in the New York Times.
- Developed and managed two multi-million dollar programs that provided naloxone and bulletproof vests for New York State law enforcement.
- Presented at national conferences, local events, and office-wide trainings on using open source intelligence and data to support investigations.
- Cultivated partnerships with universities and technology start-ups to enhance the office's technological capacity, including projects to identify illegal drug dealers on social media, developing metrics to identify bad-actor landlords, and finding social media posts about consumer fraud by training a model based on complaints submitted to the office.

Lead Researcher
Previous Positions: Research Analyst, Researcher, and Intern
Service Employees International Union 32BJ
New York, NY (Jun. 2010 - Oct. 2013)

- Led a team of researchers that supported the union's collective bargaining and new member organizing efforts in several major East Coast markets.
- Developed and executed strategic corporate campaigns by identifying appropriate tactics, relevant research, and necessary resources; significant wins include defeating Delaware's largest non-union janitorial contractor and unionizing janitorial companies at the National Naval Medical Center.
- Authored and managed the release of two papers about the conditions of New York City public school facilities, the second of which was widely covered by local news and prompted a city council oversight hearing.
- Developed union density analysis, market research, contract cost scenarios, and dossiers that included financial, legal, political, and other public information.

EDUCATION

Masters of Arts– Economics
The New School for Social Research
New York, NY (2010)

Bachelor of Business Administration– Economics
Washburn University
Topeka, KS (2008)
Summa Cum Laude; University and School of Business Honors; Leadership Studies Certificate

Certificate in Data Science
General Assembly
New York, NY (2015)

HONORS

- Coro Leadership New York (2017)
- City & State's 40 Under 40 (2016)
- New York State Office of the Attorney General's Innovation in Law Enforcement Award (2016)
- New York State Office of the Attorney General's Superior Service Award (2014, 2015)

SKILLS

Adobe Creative Suite; Amazon Web Services (S3, Redshift); Git; Python; SQL; Tableau; Qlik

OTHER EXPERIENCE

Senior Researcher
The Global Clearinghouse
New York, NY (Feb. 2009 - Apr. 2010)

Teaching Assistant
The New School for Social Research
New York, NY (Aug. 2009 - Dec. 2009)

Assistant to Operations Director
Kathleen Sebelius for Kansas Governor
Topeka, KS (Jan. 2006 - Dec. 2006)

Assistant Campaign Manager
Tiffany Muller for Topeka City Council
Topeka, KS (Feb. 2005 - Apr. 2005)

Field Area Organizer
Nancy Boyda for U.S. Congress
Topeka, KS (May 2004 - Aug. 2004)